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Enabling Dynamic Pricing of Perishables in Grocery Stores: Identifying Batches for Markdown

Master's Thesis

Espoo, July 30, 2021

Supervisor: Professor Holmström, Jan

Thesis advisor(s): D. Phil. Saarinen, Lauri and M.Sc. (Econ.) Loikkanen, Lauri

AALTO UNIVERSITY **ABSTRACT OF THE MASTER´S THESIS**

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The current inventory replenishment practice FIFO is widely adopted from all grocery retailers in the world. By applying FIFO, the older batch is placed in front on shelf. This practice aims to direct consumer purchase to the older batch. However, the appearance of multiple batches of the same product on shelf and the tendency to choose the freshest or newest batch make this current practice ineffective. In order to encourage consumer to purchase the older or near-expired batch, dynamic pricing, especially markdown pricing can be seen as a potential solution to the problem.

Although dynamic pricing has been well studied in literature, the main focus is based on SKU level. This shows a research gap for the application of dynamic pricing at batch level. The current set up in information system and product identification technology at grocery retailers does not allow for an efficient and effective dynamic pricing. The main reason is because it is impossible to identify batches of the same product with different remaining shelf life.

The proposed solution in this thesis is in a form of a 5-step operational process. This end-to-end process aims to automatically identify available batches of every SKU on shelf and be able to generate the probabilistic forecast for the amount of spoilage. At the end of the process, a new invented policy called (SR, RSL, DP) is introduced and help to categorize batches to different risk profile. Based on this classification, different discount % can be set corresponding to each risk profile.

Dynamic pricing and batch-level perishable products identification are still uncommon from current practice in grocery retailers. The demonstration and result of the Bayesian Poisson regression model in proposed operational process has proven good performance in terms of forecasting accuracy and bias. In addition, the design of the operational process is feasible and can be implemented to current real-life situation. Therefore, this thesis not only contributes to current dynamic pricing and product identification literatures, but also help to improve the current solution in practice.

Keywords: Grocery retail, perishables, shelf life, risky batches, spoilage, dynamic pricing, markdown pricing, Bayesian, Poisson regression, design science

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Life is hard !!!

This section closes a journey of 5 years of my master study of Industrial Engineering and Management at Aalto University. While writing these words, there is less than 1 hour until the deadline which I have to submit this thesis, in order to, be able to graduate on time.

This thesis is the most challenging and also exhausting journey in my life. Finally, I can finally complete it at the last minutes. I would like to express my gratitude to Professor Jan Holmström for providing me guidance with his expertise. In addition, I will always remember his help to Zoom with me even in his holiday period. I want to say thank you to Lauri Saarinen and Lauri Loikkanen for generating the data for me to perform the modelling, as well as, give a very challenging topic to work on.

Finally, I want to say thank you to my parents Lê, Vinh Trịnh and Nguyễn, Thị Thu Hà for scarifying all their lives to provide me a better education and career.

Espoo, Finland, July 30, 2021

Lê, Vinh Trung Tín

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Abbreviations

B2B	Business to business
B2C	Business to consumer
BSLP	Base stock list price
DSRP	Design science research process
EDA	Exploratory data analysis
ELPD	Expected log predictive density
EOQ	Economic order quantity
ERP	Enterprise resource planning
FIFO	First in, first out
GLM	Generalized linear model
LOO	Leave-one-out cross-validation
MAE	Mean absolute error
MCMC	Markov chain Monte Carlo
ME	Mean error
MOQ	Minimum order quantity
QR code	Quick response code
RFID	Radio-frequency identification
RMSE	Root mean square error
SKU	Stock keeping unit
(SR, RSL, DP)	Spoilage rate, remaining shelf life, discount percentage
TTI	Time temperature indicator
WTP	Willingness to pay

1. Introduction

1.1 Background and motivation

Perishables, especially foods, account for around 50% of sales in grocery retailing industry and it is the top criteria that consumers consider selecting grocery stores. (Heller, 2002; First Research, 2009). When the remaining shelf life reached and perishable products cannot be sold, they are discarded and considered as spoilage. Around 33% of food products are lost yearly. Additionally, spoilage and damage of on-shelf perishable products is estimated approximately 15% (Liu et al., 2008; Chew et al., 2009 and Nagare and Dutta, 2012). Within 31% of food waste in the United States, 10% of it is from retailers and the rest of 21% comes from households (Buzby et al. 2014). In the EU, consumer sector is also the major source of food waste which accounts for 53% (Stenmarck et al., 2016). Furthermore, an average 4.5 tons of CO_2 is generated from every ton of food waste (Wrap, 2007). Because perishable products play an important role on grocery retailers' profitability and spoilage impacts the sustainability aspect which then affects the corporate image, effective management of perishable products is necessary (Chung, 2019).

Goyal and Giri (2001) classified inventory into three categories in their study of deteriorating inventory models. The categories include deterioration, obsolescence and other (neither deterioration nor obsolescence). The value of items which are categorized as obsolescence decreases over time due to rapid changes in technology, the introduction of new generation, etc. Regarding deterioration, items which are discarded due to damage, dryness, spoilage, etc. can be classified into this category. Van Donselaar et al. (2006) and Tsiros and Heilman (2005) defined perishables as products that are particularly sensitive to preserved conditions and their values deteriorate over time with shelf life of 30 days or less.

Recently, the adoption of dynamic pricing has increased (Coy, 2000). Due to the ease of changing price online, dynamic pricing, particularly markdown pricing, are now popular in both B2B (Business-to-business) and B2C (Business-to-consumer) ecommerce

(Elmaghraby and Keskinocak, 2003). One typical example is Amazon. A lot of literatures have studied and developed optimal dynamic pricing models for perishables. Almost all of studies have confirmed the benefits of dynamic pricing in terms of profitability maximization, spoilage reduction and sustainability improvement. Despite the huge benefits of dynamic pricing, the adoption and implementation of it in brick-and-mortar grocery retailers is lacking behind (Tekin and Erol, 2017).

Due to the nature of perishability, consumers prefer to buy perishables which have considerable remaining time until they are expired (Broekmeulen and Van Donselaar, 2019). The reason for this preference is because consumers may consume fresher products and achieve greater flexibility through planning for their consumption by keeping perishables for longer time in refrigerators for example. It means consumers will pick items from a newest batch given there are multiple batches with different remaining shelf life of the same product on shelf and their price are the similar. Current inventory replenishment practice from nearly all grocery stores in the world is based on FIFO (First in, First out) rule (Tekin and Erol, 2017). It means store employees will place the batch which has the least freshness level or remaining shelf life in front and the newest at the end. The goal of this practice is to increase the chance that the customer will pick the older batches. However, this replenishment practice is destroyed due to mixing batches on shelf and consumer's attitude.

To address the problem of consumer's purchasing behavior with multiple batches of the same product on shelf, it is necessary to adopt dynamic pricing, especially markdown pricing strategy to older batches. However, the current popular usage of barcode technology for product identification in grocery retail industry does not allow for an effective dynamic pricing at batch level. Therefore, it is very important to have a solution to identify batches of perishable products, especially ones which are at risk of spoilage, Current literatures regarding dynamic pricing only focus on product or SKU (Stock keeping unit) level and only a few ones paying attention to the topic of product identification from batch level. This highlight a research gap which will be addressed in this thesis. Later on in chapter 4 (Implementation), a more detailed description and explanation of the problem and current solution in practice will be discussed following design science methodology.

1.2 Objectives and scope of the thesis

Under above discussion, the current widely adopted FIFO practice in grocery retailing industry to address multi batches on shelf with different expired dates is not effective. Optimal dynamic pricing strategy which is well-studied in literatures can be seen as a highly potential solution to this problem. However, the current information system at grocery retail and other alternatives to traditional barcode does not allow for an efficient adoption of dynamic pricing at batch level for every SKUs. Therefore, the objectives of this thesis include:

- Objective 1: Developing an automatic or partial automatic solution to identify perishable-product batches which are at risk of spoilage so that optimal dynamic pricing can be applied more effectively.
- Objective 2: Evaluating the feasibility and practicality in terms of implementation of the proposed solution to the context of grocery retail and perishable products in real life and the usefulness of it with regards to the helping the adoption of dynamic pricing.

Regarding the scope of this thesis after discussions with the expert, it is assumed that the proposed solution does not need to incorporate consumer package size, product substitution and cannibalization factors. The focus is only based on order quantity (replenishment quantity), beginning inventory of SKUs when an order is replenished and the remaining shelf life.

1.3 Structure of the thesis

Based on problems of the current solution in practice and objectives of the thesis, the structure is created with 6 chapters as follows:

- Chapter 1 (Introduction): The overview of grocery retail industry, perishable products and current practice, as well as, the necessity of identifying product batches which are at risk of spoilage is discussed. Then objectives of the thesis is also specified.
- Chapter 2 (Literature review): Literatures regarding dynamic pricing together with the identification of batches with application to grocery retail and perishables starts first to be reviewed and the conclusion on the research gap is highlighted. After that,

two statistical and machine learning methodologies and their performance assessment are studied as a part of the proposed solution. Lastly, different performance measures for evaluating predictions are inspected.

- Chapter 3 (Research methodology): The design science approach is introduced and explained together with the detailed description of the design science research process. This chapter also describes the generated data and provides the exploratory analysis.
- Chapter 4 (Implementation): By following design science research process, the problem identification, current solution and objectives of the proposed solution are first described. Then the development of the proposed solution is conducted. The chapter ends by providing the result and evaluation of the proposed solution.
- Chapter 5 (Discussion): This chapter underlines the contribution, discusses the limitations and provides suggestions for further development and research of the proposed solution.
- Chapter 6 (Conclusion): This final chapter conclude the whole thesis by summarizing the identified problem which the thesis needs to tackle, the objectives of the thesis and insight gained from the research.

2. Literature review

This section starts by reviewing literatures regarding different dynamic pricing models and ones with the application of product identification methods for perishable products. Then, a research gap of current dynamic pricing and product identification literatures when it comes to SKU and batch level was highlighted. Based on the highlighted gap, two potential solutions using statistical and machine learning methods were proposed and reviewed. Finally, the chapter ends with a brief review of available prediction measures used with the model.

2.1 Dynamic pricing for perishable products

Elmaghraby and Keskinocak (2003) provides a comprehensive review of dynamic pricing under different scenarios. Each category contains combination of inventory, shelf life, customer, multiple products and multiple stores. In general, there are three main categories of dynamic pricing literatures: Replenishment vs No replenishment inventory, dependent vs independent demand over time and myopic vs strategic customers. Within the scope of this thesis and the purpose of generated data by the expert, only the scenario "Replenishment inventory – independent demand over time – myopic customers" is relevant. In this daily operating scenario where inventory can be replenished, the link between pricing and procurement is very important. For perishable products in this scenario, the coordination of pricing together with decisions in inventory procurement and production is key. Consequently, it impacts the grocery stores' profit. For example, a too low-price setting of a perishable products may result in stockouts and lost sales while waiting for inventory to be replenished. Conversely, a too high-price setting leads to excess inventory and high inventory cost (Elmaghraby and Keskinocak, 2003).

The optimization of inventory and pricing policy of sellers who face uncertain demand and price their products periodically over time was discussed in (Federgruen and Heching, 1999; Thowsen, 1975 and Zabel 1970). The seller must decide how much inventory needs to be stocked at the beginning of the period. During the period, the demand is uncertain and is modeled as a function of price. Additionally, there are three types of associated convex cost in those models, including: ordering cost, inventory holding cost and production cost. The output of those three models is an optimal BSLP (Base stock list price) policy after considering various factors, for example: demand uncertainty, cost structure, lost sales, production lead time, etc. The policy shows that if the beginning inventory is less than the base stock level, products need to be procured or produced more and charged certain price. In case the beginning inventory is higher than the base stock level, products will not be ordered and discount needs to be applied. In such a case, the price is a decreasing function of beginning inventory. Zabel (1970) also considers other scenarios with finite selling horizon, immediate-filled orders, linear holding cost, convex production cost and lost unsatisfied demand in his paper. The key findings from the paper are that the optimal price can be formulated as a decreasing function of beginning inventory and the price and order quantity decreases gradually as the time proceeds. From Zabel (1970), other factors (backorders, inventory deterioration and late payment) is incorporated in Thowsen (1975). Given backlogged demand, linear product cost and convex holding and stock out cost, BSLP is optimal in case of partial backlogging. Based on the paper of Thowsen (1975), the assumption of freely decreasing price is added in the model of Federgruen and Heching (1999). In case the seller wants to maximize long-term profit, their findings shows that the optimal pricing policy depends on whether the price can be freely changed or only be decreased. If the price is only allowed to be reduced, the optimal strategy is to use a fixed price with order-up-to-level inventory replenishment policy. These discussed papers in this paragraph shares similar modeling assumptions, including: Uncertain demand, convex costs (holding, ordering and production) and infinite production capacity.

By taking in to account the fixed orderting cost, the inventory replenishment policy (s, S, p) is optimal with two conditions (Thomas, 1970 and Chen and Simchi-Levi, 2004). First, the demand needs to be additive within finite-time period. Second, the goal of the seller is the maximization of expected long-term profit or average of discounted profit. Regarding (s, S, p) policy, it is better to use dynamic pricing and existing inventory as instrument to manage the uncertainty in demand given the inventory level goes above the maximum threshold. In all discussed articles so far, the capacity is assumed unlimited. Chan et al. (2006) researched the partial-planning strategy in case of random demand and limited capacity. In this scenario, only price and production schedule are set at the start of the planning horizon. After that, the price and manufacturing can be changed to overcome the uncertainty in demand and inventory costs. The key finding from the work is that dynamic pricing methodology is benefitable in case of restricted capacity and the high seasonality of demand.

Rajan et al. (1992) and Biller et al. (2002) considers the use case of dynamic pricing given the deterministic demand. The focus of Rajan et al. (1992) research is based on perishable or fresh products and how dynamic pricing occur during the ordering lead time. It is assumed that the deterministic demand decreases when the remaining shelf life approach expiration, the order is delivered immediately with certain lead time and all perishable products need to be cleared during the ordering cycle. According to the cost, ordering and holding are assumed to be constant, only the spoilage cost decrease over time due to the relationship with inventory. The key findings from the study are that the price can either increase or decrease and the changed direction of price depends on the costs and the demand rate as perishable products reach the end of shelf life. If the demand rate is high, the price tends to increase. On the other hand, the price needs to be decrease gradually when the demand is low. In terms of profit, a policy of dynamic pricing outperforms the optimal fixed pricing when the demand is high given the price decrease over time. In case the price increases in t, dynamic pricing performs better than the counterpart when the inventory costs are high. Biller et al. (2002) approaches the same problem and context as Rajan et al. (1992) with the adaptation of greedy algorithm to generate the revenue function optimally for each ordering cycle. The assumption from the approach is that the revenue function has to be concave related to sales. The key findings form the study show that the dynamic pricing methodology works best when the demand is high, then decreasing over time. Conversely, it is worst to use dynamic pricing when the demand is low and then increasing over time.

All previous literatures on dynamic pricing categorize the demand into either myopic, strategic or price-dependent demand. Chung and Li (2014) argues the practicality of such classification when it comes to perishable products. The value of perishable product diminishes as the perishable products approach their shelf life. By dynamically changing the price, the sellers can provide a trade off between price and freshness to their customers. This type of demand is called need-driven demand (Chung and Li, 2014 and Chung et al., 2014). The assumption of need-driven demand is that consumers have their own desired remaining days left before expired date which follows Normal distribution. The dynamic pricing model in Chung and Li (2014) is not continuous, instead, different pricing strategies (single, two and multiple) were compared in relation to sales, profits and waste. Chung et al., 2014 studied the discount timing and its impact on grocery stores' performance (sales, expired goods, inventory aging, etc.). Chung (2019) extends his previous research by studying dynamic pricing's impact on package size. The assumption is that the package size may alter customer behavior. If the perishable products are packed in large size, the consumers may choose the batch with more remaining days before expiration as it takes more time to consume it. On the contrary, the consumers may accept soon-to-expired products if the package size is small. Furthermore, an additional comparison between dynamic pricing and a "no discount" policy was conducted. With "no discount" policy, the grocery stores apply FIFO (First in First out) rule so that the perishable products which has the least remaining days before expiration will be displayed and other fresher perishables will be kept in the storage.

Recent studies in the area of dynamic pricing examines products which have multi-generation product line. Due to the advancement in technology and shorter life cycle trend in electronics industry, companies tend to release new generations more frequent and keep several generations on the market at the same time to maximize the profitability. Bhatia et al. (2020) developed a dynamic production-pricing model taken into account internal competition between different generations of the same product. Findings from the study indicate that sales of older generation can be improved by increasing innovation level, but the gap between the oldest and the newest generations must be kept at minimum in terms of innovation. Regarding customer segment, the sales of older generations decrease when the number of innovation sensitive customers is higher and vice versa. In general, the proposed jointly dynamic production-pricing policies performs significantly better than fixed production-pricing policies.

In general, dynamic pricing for perishable products has been well studied in literatures since the late 1900s. However, almost all the articles in this subject mainly focus on SKU level and there are only a few literatures paying attention to the topic of product identification from lower granularity perspective, for example batch level or item level. Regarding item level, Li et al. (2006) and Lin (2003) developed dynamic pricing models for perishable foods with enabled-traceability system. This system can provide more accurate estimates of remaining shelf-life information. Buisman et al. (2019) examined discounting and replenishment strategies for meat product at grocery retail stores. He found that the use of shelf-life information which is able to be dynamically adjusted makes markdown pricing strategy for perishables be more effective than predefined fixed shelf life in terms of both profitability and spoilage. The same approach is adopted in the studies of Gao et al. (2020), Herbon et al. (2014), Liu et al. (2008), Piramuthu and Zhou (2013) and Zhou et al. (2009). In general, all these kind of papers takes advantage of the advancement in product identification technologies using sensors, for example, TTI (Time temperature indicator) and RFID (Radio frequency identification). These enabled technologies allow to automatically capture all related production information (humidity, temperature, etc.) in real time and can be applied to item level by simply attaching identification tag. Based on captured information, retailers can make pricing decisions dynamically. Although the use of advanced identification technologies is feasible in theory and research, the widely adoption of it to current grocery retail industry is questionable due to the high cost in initial investment of new information systems and individual tag as compared to the other cheap and popular barcode. This approach is also excluded from the scope of this thesis.

According to batch-level identification, only the research from Pantsar (2019) could be found. In his master thesis, a process for estimating the batch balance of perishable products was developed using mathematical method to solve system of equations in the form of matrix. After that, a simulation model was constructed with input from various inventory depletion model and historical store data. The result of the thesis is a process which is able to provide the estimates of batch balance for product and location. Although the thesis correctly addresses batch level, there is a lack of connection with dynamic pricing.

In conclusion, there is a research gap in the studies of dynamic pricing in the context of perishable products at batch level of SKUs. By adopting and modifying the idea from Bhatia et al. (2020), multi-generation products can be seen as perishable product batches with different replenishment date or remaining shelf life. Then the price of older batches should be lower as compared to newer batches, in order to, maximize the profitability of all batches of a SKU on shelf. To do it, perishable product batches which are at risk of spoilage must be identified. In the next section, two statistical models will be discussed as an intermediate solution to the problem without using current advanced technologies.

2.2 Poisson regression model

Poisson regression is just like traditional multiple regression with one exception that is the dependent variable has count data. The count data means all values in response variable are only in the form of non-negative integers (0, 1, 2, etc.). In addition, this countable dependent variable follows the Poisson distribution. Large count values are unlikely to happens with Poisson distribution (Tripathi, 2017).

Poisson regression, together with other regression models for count data (negative binomial model, hurdle model, zero-inflated Poisson models, zero-truncated Poisson models, etc.), is a special case of GLMs (Generalized linear models). In the early 1970S, GLMs emerged from many statistical literatures (Nelder and Wedderburn, 1972).

2.2.1 Poisson distribution and the regression model

Although there are many regression analysis literatures which briefly mention about Poisson regression, the book written by Cameron and Trivedi (1998) is dedicated to this model. Thus, formulas and discussions in next paragraphs are mainly based on this source. The root of Poisson regression is Poisson distribution. Poisson distribution is a probability distribution which models the y events with below formula:

$$\mathbf{Pr}(\boldsymbol{Y} = \boldsymbol{y} \mid \boldsymbol{\mu}) = \frac{\boldsymbol{e}^{-\boldsymbol{\mu}} * \boldsymbol{\mu}^{\boldsymbol{y}}}{\boldsymbol{y}!} (\boldsymbol{y} = \mathbf{0}, \mathbf{1}, \mathbf{2}, \dots) \tag{1}$$

There is only one single parameter in Poisson distribution which is named as μ. It is considered as incidence rate per unit of exposure, for example: time, population, volume, etc. and has to be greater than 0. One important assumption of Poisson distribution is that the expected mean of random variable Y has to be equal to its variance.

Suppose a sample data with n observations (y_1, y_2, …y_n) follows Poisson distribution with incidence rate μ and is explained by k regressors. We have:

$$\mu = t * \boldsymbol{e}^{(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{X}_1 + \cdots + \boldsymbol{\beta}_k \boldsymbol{X}_k)} \tag{2}$$

Here, β_0 is the intercept and $\beta_1, \dots, \beta_k$ are called regression coefficients which are unknown parameters and estimated from the data. The estimated regression coefficients are under notation $b_1, \dots, b_k$. In general, the Poisson regression model has the below form:

$$\mathbf{Pr}(\boldsymbol{Y}_i = \boldsymbol{y}_i | \boldsymbol{\mu}_i, \boldsymbol{t}_i) = \frac{\boldsymbol{e}^{-\boldsymbol{\mu}_i \boldsymbol{t}_i} (\boldsymbol{\mu}_i \boldsymbol{t}_i)^{\boldsymbol{y}_i}}{\boldsymbol{y}_i!} \tag{3}$$

$where\ \mu_i = t_i \mu(x_i' \beta) = t_i e^{(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k)}$

In above formula, the exponent of the regression coefficient β_k represents the multiplicative effect of k-th predictor on the mean. It can be interpreted as the mean is multiplied with the factor e^{β_k} with an increase of 1 unit in predictor x_k.

The regression coefficients in the Poisson model with link log as being discussed above is solved by adopting maximum likelihood method. The natural logarithm of the likelihood function is in the form:

$$\mathbf{ln}[\boldsymbol{L}(\boldsymbol{y}, \boldsymbol{\beta})] = \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} \boldsymbol{y}_i \, \mathbf{ln}[\boldsymbol{t}_i \boldsymbol{\mu}(\boldsymbol{x}_i' \boldsymbol{\beta})] - \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} \boldsymbol{t}_i \boldsymbol{\mu}(\boldsymbol{x}_i' \boldsymbol{\beta}) - \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} \mathbf{ln}\,(\boldsymbol{y}_i!) \tag{4}$$

By taking derivatives of the log-likelihood function with each of regression coefficients and setting the derivatives to 0, the above likelihood equation can be formed. The term maximum likelihood means an algorithm is iteratively used to find set of regression coefficients, in order to, maximize the log-likelihood. This method performs slowly as the size of data increases. However, this is not a big issue with today power of computing.

In this thesis, the Poisson regression model is implemented in R (R Development Core Team, 2008). The model is fitted using glm() function in stats package (Chambers and Hastie, 1992). Figure 1 shows critical arguments of glm() function. Only three arguments were used in the development of the proposed solution in chapter 4, including: formula, data and family. The formula takes the regression model as input. The data means training data and the family argument here is "poisson". The link log is set as default when selecting "poisson" family. Other arguments are kept as default.

```
glm(formula, data, subset, na.action, weights, offset,
  family = gaussian, start = NULL, control = glm.control(...),
  model = TRUE, y = TRUE, x = FALSE, ...)
```

Figure 1. glm() function in R

2.2.2 Model performance assessment

In this subsection, three performance measures to assess the fitted model will be introduced. Later on, those measures are then implemented in chapter 4.

R^2 (or called as "R squared") is the coefficient of determination. It is a statistical measure which could be interpreted as the proportion of variance in the response variable explained by predictors or by the fitted model. R^2 ranges from 0 to 1. If the measure is close to 1, it implies nearly perfect relationship between the fitted model and the data. On the contrary, a close-to-0 R^2 indicates that the average or mean of the data is equivalent to the fitted model (Saunders et al., 2012).

Pearson (1900) has introduced P value since 1900. It is considered as the most important factor in the summary of regression models or statistical test. According to Wasserstein and Lazar (2016), P value is the probability in which the null hypothesis is true.

Additionally, it also indicates the compatibility of observed data with a specific statistical model and focuses on to study the null hypothesis. The greater the incompatibility of the data with the null hypothesis, the smaller the P value. Reflecting to the Poisson regression model, the null hypothesis for each model parameters is that the coefficient is equal to zero or has no effect. If an independent variable has a low p-value with associated regression coefficients, that predictor's change is likely to related to the changes in the dependent variable.

AIC (Akaike information criteria) is a measure computed on training data set after fitting the model. It cannot be used for predicting performance between datasets and models (Hyndman, 2013). Within information criteria, AIC is common and often used in forecasting and time series analysis. AIC takes below form (Gelman et al., 2013):

$$\boldsymbol{AIC = 2k - 2\log p(y|\hat{\theta}_{mle})} \tag{5}$$

where $p(y|\hat{\theta}_{mle})$ is the estimate of maximum likelihood of training model and k represents the number of parameters in the model. The smaller AIC is, the better the model. One of advantage of this information criteria is that it penalizes the models with large number of parameters. If a predictor is added to the model with less value, the model will be penalized.

2.3 Bayesian Poisson regression model

2.3.1 Overview of Bayesian methodology

Statistics is divided based on two fields: Frequentist and Bayesian. The Bayesian statistics dates back to the 1700s which has a long history with controversy. The important difference between these two fields is that Bayesian statistics utilizes prior knowledge and observed data, whereas frequentist statistics use only observed data. This key difference in the adoption of prior knowledge which can be subjective makes Bayesian statistics undergo such a long period of criticism. In addition, confidence interval is used by frequentists and credible interval is used by Bayesians. Confidence interval is generated by randomly sampling from a population, then the percentage of the samples contain true parameter is concluded. The confidence interval does not allow to make the probability statements regarding parameters. On the other hand, the credible interval is a probability statement which conclude the chance in which the interval contains the true parameter. It allows to obtain a probability distribution of posterior across all possible values of parameters given the model and observed data. One can easily generate the probability of the value of parameter in any interval (O'Hagan and Luce, 2013 and Recchia, 2012).

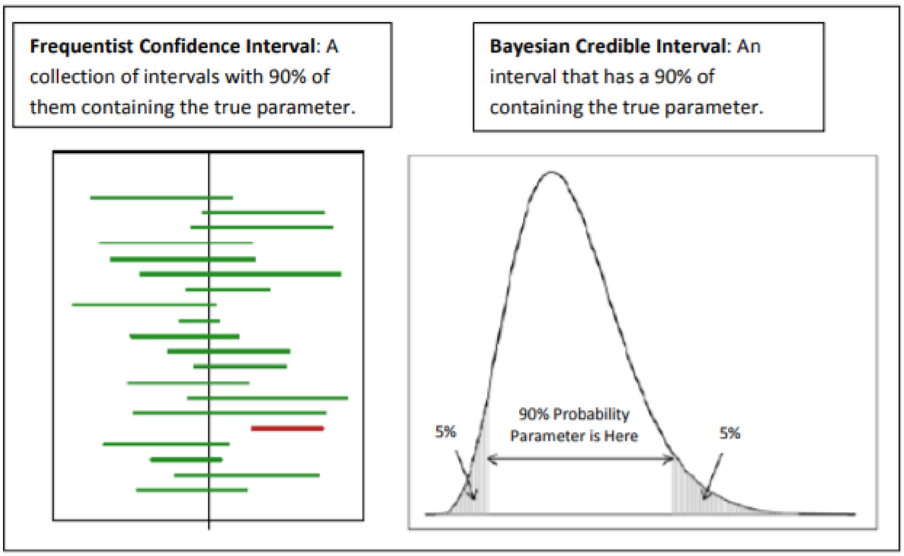

Figure 2. Confidence vs credible intervals (adapted from Recchia, 2012)

Refer to Bayesian literatures (Gelman and Hill, 2007 and Gelman et al., 2013), the objective of the Bayesian model is to evaluate posteriors with calculated unknown statistic based on a likelihood function and a specified prior distribution. Not only it helps to explain the uncertainty in the dependent variable given unknown parameter θ, but also the uncertainty in prior of parameters. Regarding regression models with dependent variables y and independent variables x, the goal of Bayesian method is to update the prior belief about the parameter θ using the model and data. The prior means our belief about the parameters before observing the data. It can, for example, come from expert judgement. The posterior is also our belief about the parameters, but after observing the data. This relationship is based on Bayes' theorem given by:

$$\boldsymbol{p(\theta|y)} = \frac{\boldsymbol{p(y|\theta)p(\theta)}}{\boldsymbol{p(y)}} \tag{6}$$

The above formula can be interpreted as the posterior probability distribution $p(\theta|y)$of parameter θ given observed data is equal to the likelihood function $p(y|\theta)$ multiplies with the prior $p(\theta)$ and divided by the marginal likelihood p(y). The term p(y) in the denominator, also called normalizing constant, is the average of likelihood across parameters in the model with weighted their probabilities. Because this constant does not depend on parameter θ, only the numerator of Bayes' formula is focused when updating the data. With reference to regression models, independent variables can be included into Bayes' formula as below function:

$$\boldsymbol{p(\theta|y,x) \propto p(y|\theta,x)p(\theta|x)} \tag{7}$$

$p(\theta|y,x)$ is the likelihood. Precisely, given the observed independent variables x, it is the joint probability of the dependent variable y for all possible values of all parameters θ. In addition, it depicts the generating process of data which produce the observation. Regarding parameters, this likelihood is not a probability density function and does not add up to 1. $p(\theta)$ or the prior is the probability distribution which represents the uncertainty from unknown parameters θ before observing data. In order to prevent extreme estimates of regression coefficients, informative prior information can be achieved from the incorporation of previous research Korner-Nievergelt et al. (2015). Lastly, the posterior $p(\theta|y,x)$ is the joint probability distribution which incorporates the updated knowledge from observed data. The posterior is also the aim when fitting a Bayesian regression model.

2.3.2 Estimating Poisson regression models

In this thesis, Stan modelling language and R was employed to develop the Poisson regression model. Stan was developed with the aim to work reliably and efficiently with models which contain high dimensional posterior distributions. Of course, it can also be able to work easily with simple models (Hoffman and Gelman, 2014 and Stan Development Team, 2017). Apart from Stan language itself, users can use Stan in R, Python or other languages. As R is primary language to be used in this thesis, the package "rstanarm" was adopted.

With "rstanarm" package, a wide variety of models can be fitted, including regression models (Poisson, etc.) using Stan estimation engine. The advantages of adopting "rstanarm" are that it is user-friendly and offer a wide range of default settings which allow an easy implementation when specifying regression models. In comparison to other Bayesian estimation packages in R like JAGS or BUGS, Stan is outstanding in terms of computing power (Spiegelhalter et al., 1996).

In simple models, the posterior distribution can be calculated analytically. However, most of the times, the posterior distribution has to be approximated using sampling techniques by simulating draws from posterior distribution. By developing the Poisson regression model, MCMC (Markov Chain Monte Carlo) simulation technique was selected. In brief, the algorithm of MCMC uses the chain of states where the position of the upcoming state depends on the location of the current state (Markov chain), so as to, find the shape of the distribution of the desired posterior. In order to check whether or not the algorithm behaves properly, the convergence to the same distribution of multiple chains with different initial values are checked (Gelman et al., 2013 and Stan Development Team, 2017).

2.3.3 Model performance assessment

Different from popular model performance assessments (R^2, AIC, BIC, etc.) in non-Bayesian regression models, Bayesian regression models use different metrics to evaluate the performance of fitted models. Two assessment metrics used in this thesis includes $\hat{R}$(or called R hat) statistic and elpd_loo estimate.

According to Gelman et al. (2013), $\hat{R}$ or R hat statistic (also known as the potential scale reduction factor) is used to check the convergence of the chains. The idea behind of this statistic is that it compares the variation within the chains with the variation between the chains. If the variance between the chains is approximately to the average variance within chains, the estimated $\hat{R}$ becomes close to 1. In other words, all chains behave similarly and converge to the same area. Besides using $\hat{R}$ statistic, there are other visualization methods to examine the convergence, for example bayesplot package in R provides many types of MCMC visualizationse (Gabry and Mahr, 2017) which could be used together with rstanarm package while modelling. However, the use of plots is impractical when the model contains many parameters. In brief, it is important to ensure that every $\hat{R}$ statistic value in the model needs to be below the threshold 1.1 (Gelman et al., 2013).

Predictive accuracy is a useful metric to compare, select and average models after fitting a Bayesian model (Geisser et al., 1979 and Vehtari et al., 2012). Before defining elpd_loo estimate, it is worth to mention ELPD. ELPD stands for expected log pointwise predictive density and is used to measure the prediction accurary. The elpd_loo is the Bayesian LOO (Leave-one-out cross-validation) estimate of ELPD. It is an estimate of out-of-sample fit of predictions and can be calculated by aggregating N individual pointwise log predictive densities. The natural logarithm of predictive densities can be either positive or negative because probability densities take values of smaller and larger than 1. This value needs to be 0 or negative (Vehtari et al., 2017).

2.4 Performance measures of predictions

In this section, literatures on performance measures of forecasting will be discussed. Described performance measures will be then used to validate difference models from different design of proposed solutions later on in chapter 4. As the primary goal of this thesis is based on the identification of risky batches on shelf through forecasting the amount of spoilage, performance measures used for forecasting or time series analysis field should be adopted. Two performance measures category which is popular in forecasting literature include forecasting accuracy and bias. Next, specific measures within each category will be described.

2.4.1 Forecasting accuracy

Obviously, forecast accuracy is one of most important and mostly used measures in both practical and research applications. Hyndman and Koehler (2006) classified and described various measures in his paper. There are four main categories or group of measures: Scale-dependent measures, measures based on percentage errors, measures based on relative errors and relative measures. Among listed measures, scale-dependent and percentage-errors measures are widely adopted. However, only measures in scale-dependent categories can be adopted in this thesis because percentage-based measures (also a type of scale-independent) in general cannot be used in case of small counts and there is the appearance of 0 values (Gardner, 1990) which occurs in the generated data of this thesis. One of advantages of scale-dependent measures (RMSE, MAE, etc.) is that both time series in the comparison must have the same unit of measures. However, this advantage is irrelevant in relation to the generated data in this thesis which will be discuss in chapter 3 because all the datasets for different products has the same structure and unit of measures. In the study of Chai and Draxler (2014), a detailed comparison between RMSE and MAE is described. RMSE has a quadratic term of errors in its formula and it will penalize large deviation from the actual value. Whereas the same weight to all deviations is applied in MAE. That is why RMSE value is always bigger than MAE given the same data and estimator. However, it is noted that there is no single perfect measure, thus a combination of measures is better. All in all, it is reasonable to utilize RMSE and MAE performance measures of scale-dependent category in this thesis.

2.4.1.1 RMSE

RMSE formula is given as:

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\boldsymbol{f}_i - \boldsymbol{y}_i)^2}{\boldsymbol{n}}} \tag{8}$$

(where f_i is the forecast of sample i, y_i is the actual value of sample i and n is the sample size)

RMSE measures the prediction errors from residuals which are the difference of fitted values from the actual values. The above formula of RMSE can be interpreted as the square root of average errors (per data point) from quadratic of deviation between fitted values and actual values. The goal of RMSE is to quantify the spread of residuals. Additionally, it shows how the sample (data) is allocated around the fitted regression line. RMSE is an accuracy measure which aims to compare prediction errors of different models of a specific dataset (not against other datasets) and is scale-dependent (Hyndman et al., 2006).

2.4.1.2 MAE

MAE formula can be expressed as:

$$\boldsymbol{MAE} = \frac{\sum_{i=1}^{n}|\boldsymbol{f}_i - \boldsymbol{y}_i|}{\boldsymbol{n}} \tag{9}$$

(where f_i is the forecast of sample i, y_i is the actual value of sample i and n is the sample size)

As like RMSE, MAE also measures prediction errors from residuals which is calculated by taking the difference between fitted values from the estimator and the actual values. From each paired observations, the absolute deviation is aggregated for the whole sample and averaged by the sample size. The main difference between RMSE and MAE is that it takes absolute value from the deviation, instead of, quadratic. MAE is also scale-dependent (Hyndman et al., 2006).

2.4.2 Bias

Bias in forecasting can be defined as the tendency in which the forecast is over or under actual values in overall. Positive bias (also known as over-forecasting) means generated predictions from a forecasting model are greater than actual values. Conversely, negative bias (under-forecasting) is the situation where forecasts are lower than actual values (Utley, 2011). Different from forecasting accuracy measures, there are less literatures and measures when it comes to forecasting bias. One of most widely adopted forecasting bias measures is ME (Mean error). The formula of ME is given as:

$$\boldsymbol{ME} = \frac{\sum_{i=1}^{n}(\boldsymbol{f_i} - \boldsymbol{y_i})}{\boldsymbol{n}} \tag{10}$$

(where f_i is the forecast of sample i, y_i is the actual value of sample i and n is the sample size)

ME is not a perfect measure for forecasting bias. It contains limitation in which there is a tendency of cancellation of each other between positive and negative errors. However, it is still a useful measure to find out systematic positive or negative bias (Utley, 2011).

3. Research Methodology

In this section, the introductory to the design science research and its process are presented. In addition, a brief comparison between design science research and other traditional research methods is also discussed. Finally, the data used for the modelling is described and analyzed in detail.

3.1 The design science research methodology

Design science is a practical research methodology which is popular in engineering research because it emphasizes on the effectiveness, applicability and incrementality of the solutions to the problems (Peffers et al., 2007). The purpose of design science is to create innovations based on ideas, practicalities, technical capabilities to real world problems (Hevner et al. 2004). The difference between explanatory research and design science research is that the former aims at understanding and explaining the reality and the latter tries to develop the artifact or the proposed solution to solve the focal problem, hence it bridges the gap between theory and practice (Holmström et al., 2009). According to (Hevner et al. 2004), existing theories contribute partly on the development and creation of artifacts and the rest is based on the experience, creativity, intuition, etc. of researchers. (Holmström et al, 2009; Öhman et al., 2015). Essentially, design science is thus to understand the real-world problem and develop and create proposed solution (design artefact) to achieve several sorts of specific objectives (Holmström et al, 2009; Öhman et al., 2015).

In order to create the design proposals, CIMO logic was employed. CIMO stands for Context, Intervention, Mechanisms, and Outcomes and these four key concepts help to develop those artefacts (Denyer et al. 2008). In brief, the CIMO-logic can be understanded as investigating and applying Interventions (I) to the problems in Context (C) which needed to be addressed, so as to achieve specific Outcomes (O) through mechanism (M) (Denyer et al. 2008; Holmström et al, 2009). With CIMO analysis, the mechanisms are identified with not only intended outcomes, but also unintended outcomes. Based on the mechanism identification, a theory which explains how such intervention generate outcomes from problem in context can be developed (Holmström et al, 2009; Gregor and Jones, 2007). Regarding this thesis, by following CIMO logic, the design proposition can be described as the use of Bayesian Poisson Regression modeling as an (Intervention) to achieve efficient and automatic dynamic pricing process (Outcome) by addressing identification issue of product batches that are at risk of spoilage (Mechanism) within grocery retail and perishable products (Context).

In this thesis, the well-known and widely cited design science research methodology (DSRM) process adapted from Peffers et al. (2007) will be adopted. DSRM process is an iterative six step process, including: Identify problem and motivate, define objectives of a solution, design and development, demonstration, evaluation and communication. Below are the description and explanation of each steps.

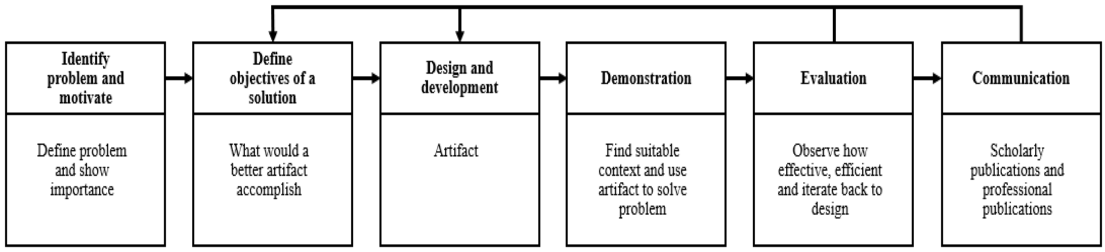

Figure 3. Design science research process (adapted from Peffers et al. 2007)

Identify problem and motivate is the first step of the process and it requires specific research problem to be defined and the value of the solution to be justified. By justifying the value of the solution, it helps to motivate the researcher and to clarify the reasoning of the researcher regarding the problem and the solution.

Define objectives of a solution after identifying the problem with the practical and realizable knowledge. The objectives of the solution can be quantitative or qualitative. According to quantitative objectives, it is needed to show that the artifact is better than the current one with some specific criterias. Regarding qualitative objectives, it is necessary to describe how the desired solution supports the current solution to the specified problem.

Design and development are the creation of the artefact. The type of the artifact varies from models, constructions, methods, etc. In order to perform this step, the knowledge of theory, the functionality and architecture of the artifact is needed to develop the solution.

Demonstration means the presentation of how the artifact solve the addressed problem. Proof, experimentation, simulation, etc. can be a type to demonstrate the solvability of the artifact.

Evaluation is needed to measure how well the artifact performs to solve the addressed problem. It can be supported by suitable analysis techniques and metrics. There are many ways in which this step could be conducted, for example: the comparison of quantitative measures (time, cost, availability, etc.), logical proof, empirical evidence, etc. This step is also a milestone step in which the researcher needs to decide whether or not the design and development step need to be iterated, in order to, improve the effectiveness of the artifact. If the iteration cannot be conducted, the present result can be communicated and left for further improvement projects.

Communication. In this final step, all aspect of the research from the problem, the artifact, the design, the effectiveness, etc. are communicated to researchers, practitioners, etc. in the form of research publications through articles, journals, etc.

3.2 Data

In this section, it first describes how the data has been generated, as well as, the components, characteristics and definition of all products and variables. After that, a preliminary exploratory data analysis will be conducted to gain better insight from the provided dataset before moving to modelling task.

3.2.1 Data generation and overview

The data used in this thesis has been provided by the contact expert and guaranteed that it mimics the real-life data from grocery stores. The dataset includes four-year time series at daily level for each of the four pseudo products. In total, there are 1460 days (data points or rows) per product in the dataset. Every row in each of created product datasets represents all relevant records at SKU level. However, the created data can be transformed into SKU and batch level data which will be discussed in section 4.3.2.2. The four products are named as A, B, C and D. According to Table 1 and Table 2, Product A is characterized as high volume with average 10 sales units per day, high volatility and short shelf life (5 days). Although product A has high daily volume and no day with 0 sales, the % of spoilage over sales is considerably high with 60% on average. Product B is characterized as low volume with average 2 sales units per day, low volatility and short shelf life (also 5 days). It has low daily volume and second highest number of zero-sales day which shows a sign of intermittent demand, in addition the % of spoilage over sales is the highest within 4 products with 100% on average. Product C is characterized as high volume with average 12 sales units per day, high volatility and long shelf life (14 days). It has highest daily volume and no day with 0 sales, the % of spoilage over sales is also the lowest with approx. 17% on average. Product D is characterized as low volume with average 2 sales units per day, low volatility and long shelf life (also 14 days as product C). It has low daily volume and highest number of zero-sales day which shows a sign of highly intermittent demand, the % of spoilage over sales is significant with 50% on average. Table 1 provides 7 variables of each product. However, the 3 variables "Price", "Purchase cost" and "Holding cost" are excluded from the scope of this thesis. "Replenishment interval" means a batch of a product is replenished in a fixed and frequent interval, for example product A batch will be replenished in every 3 days period. The quantity of each batch is determined by the expert but must be a multiple of MOQ (Minimum order quantity). The "Lead time" variable is the number of days form ordering batch to delivering and replenishing it on the shelf.

Table 3 provide a sample of product A dataset. There are 7 variables in total: Forecast, Sales, Inv_hand, Order_qty, Replenish_qty, Obs_inv_qty and review_date. "Forecast" variable is simply naive forecast and it is not relevant in the modelling task. "Sales" variable is generated so that it follows product characteristics (high/low volume and volatility). "Inv_hand" means ending inventory of a day with the formula $\mathbf{Inv\_hand_t} = \mathbf{Inv\_hand_{t-1}} + \mathbf{Replenish\_qty_t} - \mathbf{Sales_t}$. "Order_qty" variable is the number of ordered products at day t. It has to be a multiple of MOQ set in product characteristics table. "Replenish_qty" means replenishment quantity. Order quantity is turned into replenishment quantity after a specific lead time (here the lead time are the same for all products with 2 days). "Obs_inv_qty" or observed inventory quantity is the amount of spoilage at the end of shelf life. "review_date" is the date when a batch is ordered.

Table 1. Product characteristics

	Product			
	A	B	C	D
Description	High volume High volatility Short shelf life	Low volume Low volatility Short shelf life	High volume High volatility Long shelf life	Low volume Low volatility Long shelf life
P (price)	5	5	5	5
C (purchase cost)	2	2	2	2
h (holding cost)	0.4	0.4	0.14	0.14
L (shelf life days)	5	5	14	14
Target availability	0.95	0.95	0.95	0.95
Replenishment interval	3	3	4	7
MOQ (minimum order quantity)	6	4	6	6
Lead time	2	2	2	2

Table 2. Product sales and spoilage summary

Product	Average daily sales	% Zero-sale day	Average daily spoilage	% of average daily spoilage over sales
A	10	0.00%	6	60.00%
B	2	13.49%	2	100.00%
C	12	0.00%	2	16.67%
D	2	14.11%	1	50.00%

Table 3. Example of provided raw dataset of product A

Forecast	Sales	Inv_hand	Order_qty	Replenish_qty	Obs_inv_qty	review_date
10	13	23	54	0	0	1
10	12	11	0	0	0	0
10	8	57	0	54	0	0
10	11	46	30	0	0	1
10	7	30	0	0	9	0
10	6	54	0	30	0	0
10	11	19	54	0	24	1

3.2.2 Exploratory data analysis

In the beginning of EDA, daily sales per each product are analyzed and combined together through the usage of histogram and box plot. As can be seen from Figure 4 and Table 4, Product C has highest daily sales value with around 12 units but it also has the highest volatility (standard deviation). Product A follows by 10 units in daily sales on average and has the second standard deviation. Product B and D are almost identical in terms of daily sales for both mean volume (2 units) and volatility (1.42 and 1.41).

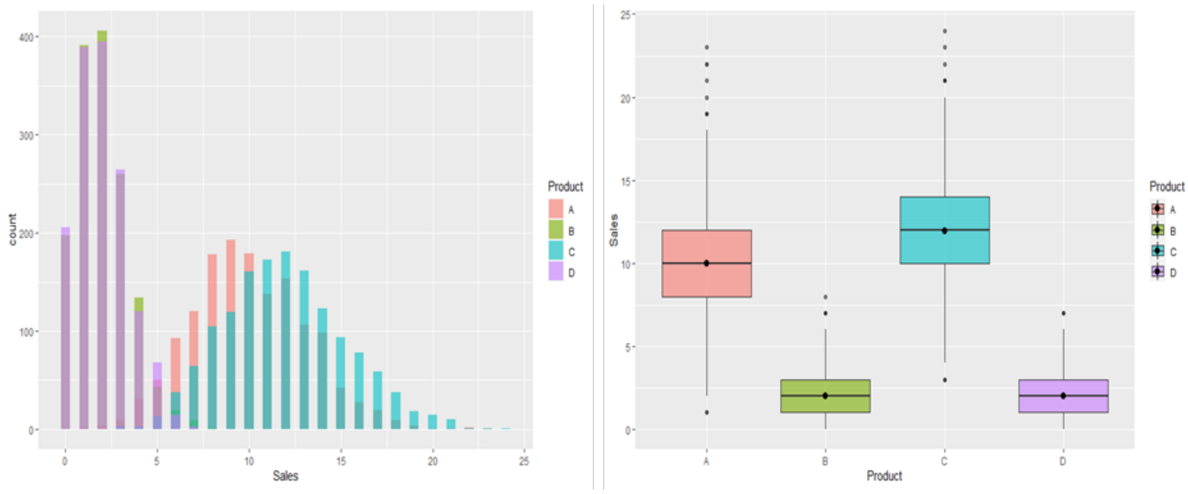

Figure 4. Analysis of daily sales per product through histograms and boxplots

Table 4. Summary statistics of daily sales for each product

Summary Statistics of Daily Sales							
Product	**Min**	**Q1**	**Mean**	**Median**	**Q3**	**Max**	**Standard Deviation**
A	1	8	10	10	12	23	3.15
B	0	1	2	2	3	8	1.42
C	3	10	12	12	14	24	3.33
D	0	1	2	2	3	7	1.41

Figure 5 investigates the relationship between replenishment quantity and spoiled quantity for each product. Although each product has different replenishment quantity and spoiled quantity. All the scatter plots and regression lines show the same upward trend. Based on those plots, it could be interpreted as the number of spoiled products will increase if grocery stores increase the order quantity (replenishment quantity).

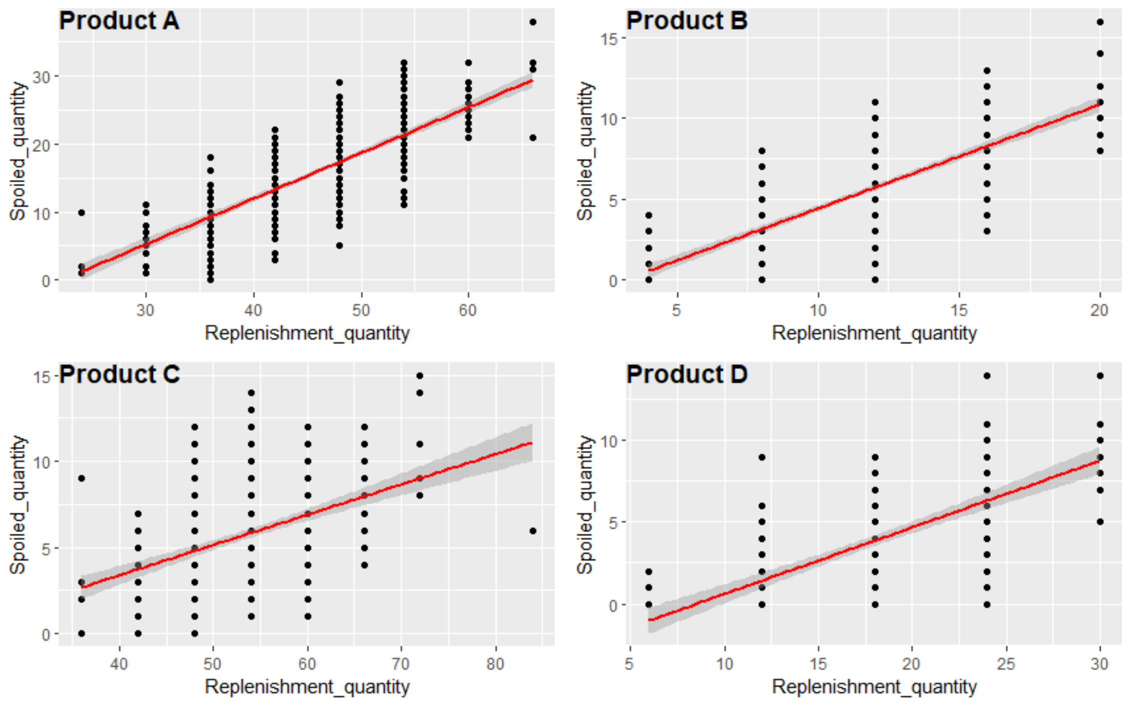

Figure 5. Relationship between replenishment quantity and spoiled quantity for each product

Finally, it is worth to analyze the spoilage rate on batch level for each product. With reference to Table 5 product B has the highest mean spoilage rate and it varies greatly between batch (highest standard deviation). From these figures, it could be easily seen that ordering decision of product B has problem as a large portion (nearly half) of an ordered batch will be thrown away by the end of the shelf life. Product A follows product B by having 34% mean spoilage rate, but the rate is more consistent from batch to batch than product B. In terms of spoilage, product C seems to perform best with the lowest mean spoilage rate. It reflects that product C is a high volume with long shelf-life product. Product D also has quite low mean spoilage rate (second lowest).

Table 5. Summary statistics of spoilage rate for each product

Summary Statistics of Spoilage Rate per Batch							
Product	**Min**	**Q1**	**Mean**	**Median**	**Q3**	**Max**	**Standard Deviation**
A	0%	27%	34%	33%	43%	60%	11%
B	0%	33%	44%	50%	58%	100%	21%
C	0%	7%	11%	10%	14%	26%	5%
D	0%	8%	19%	17%	29%	75%	15%

In conclusion, it is consistent between EDA and product characteristics and assumptions. Long shelf-life product tends to have lower spoilage rate, in comparison to, short shelf-life one. In addition, low-volume-product batch has higher chance to be spoiled compared to high-volume-product lot.

4. Implementation

Based on the design science research process, this chapter first describes the current solution, then identifies the problem in context and sets objectives for the proposed solution. After that, a detailed of the design and development of the proposed solution is explained. At the end of the chapter, results from the proposed solution are presented and the proposed solution is evaluated based on certain criteria.

4.1 Current solutions and problem identification

For perishable products which have multi batches on shelves, batches have different stocks balance with different freshness level. In this situation, current practice from nearly all grocery stores in the world is based on FIFO rule (Tekin and Erol, 2017). It means store employees will place the batch which has the least freshness level or remaining shelf life in front and the newest batch is located at the end. When a new batch comes, it needs to be replenished and placed in the right order according to FIFO rule. The goal of this practice is to increase the chance that the customer will pick the older batches.

Because of the nature of perishability, consumers prefer to buy perishables which have considerable remaining time until they are expired (Broekmeulen and Van Donselaar, 2019). The reason for this preference is because consumers may consume fresher products and achieve greater flexibility through planning for their consumption by keeping perishables for longer time in refrigerators for example. Thus, WTP (Willingness to pay) of consumers decrease simultaneously with the proceed in remaining time until "Best before" date (Tsiros and Heilman, 2005). It means, whenever a consumer purchases perishable products, he/she regularly checks the price and the expired date on the package. It has low chance that such consumer will purchase the shorter remaining shelf-life product/batch given the same price applied to SKU level.

To address this problem, there are three identified current practices. First, many grocery retail's policy do not allow to place many products with various "Sell by" date on the same shelf. Thus, only one same-expired-date group of products in each SKU can be kept on shelf (Tekin and Erol, 2016). The expert also provides an example with the selling of cheese products at a department store in Finland. The replenishment rule for cheese products is that there should not be more than one batch at any time and any batch must be cleared in two weeks. It means, by the end of the terminated or expired date which is known for certainty, the displayed batch needs to be cleared before a newer batch is replenished. In order to clear the near-expired batch, the department store calculates and applies the markdown percentage. Here, the markdown pricing can be applied automatically according to the remaining shelf life and/or quantity. It is also possible to markdown the price several times until the perishables are discarded. This first practice may work rather well to reduce the amount of spoilage and improve the profitability. However, it can only be applied in the context of single batch on shelf.

The other two current practices can address the problem of multiple batches on shelf. The second current practice is similar to the first one in case of single batch. That is a common pricing policy is applied to SKU level. It means all batches of in the same SKU with different remaining shelf life receives the same price or discount. In reality, this practice is currently adopted due to the simplicity in implementation. However, it is considered as a failure due to the lack of effectiveness. The reason is due to the consumers' attitude to purchase the newest batch as discussed in the beginning of this section. The third current practice is that discount is given manually to target batch which is soon to be expired. According to the expert regarding the daily operational markdown pricing process, store employees in the grocery retailers need to go to the shelves, then check manually the balance of each batch for every perishable product. Based on the information of remaining shelf life from the system and the balance of the batch from the manual checking, the store operations manager or the employees will determine whether or not the batch needs an attached discount label. As a current practice, only one-time 30%, 50% or 70% discount label is applied to the unit when the product will soon to expire (normally 1-2 days left). This expert's opinion regarding one time discount when the remaining shelf-life approaches "Sell by" date is in line with the study conducted by Chung and Li (2013). In that study, interviews with grocery store managers in Korea also reveals one time discount of either 20%, 30% or 50% is applied when 20-30% of shelf life remained.

Despite the capability to be automized of the second current practice, it is almost impossible to apply markdown pricing in an automatic and dynamic way to target batch of each SKU. If the grocery store markdowns the price of a perishable product, the price all batches on shelf regardless of expired dates will be deducted by the system. The reason is that every product in grocery stores is assigned to a linear 1-dimension barcode. Due to the design limit, this barcode cannot store more information than the product name. That is why the information system in grocery stores cannot identify old and new batches of the same product. As discussed in the literature review in chapter 2, there exists various technologies (RFID, etc.) and types of barcodes which can address this issue. However, the variable cost of each RFID or other types of advanced barcode tag and the investment in information systems are huge. Additionally, this requires a significant change in the whole industry and its supply chain. While waiting for such frog leap change, grocery stores are still practicing the intermediate solution (the third current solution) to overcome the issue as they are simple, easy to be implemented and have low investment capital.

There are three drawbacks with this third current practice. Firstly, the arrangement of batches on shelf following FIFO rule and the batch balance checking requires manual task. It means such kind of task requires human resources to do it and it incurs labor cost. This cost is in the type of salary or rates, for example €/hour. By assuming or calculating how many products are checked by the store employee within a certain time period, we can get the unit cost (€/product) for performing a manual check per product. (Aguirregabiria 1999, Chen and Hu 2012 and Levy et al. 1997) provides evidence about considerably high cost related to price revision, specifically, in the grocery retail industry. Activities associated with price revision include: labor, supervision, printing label, etc. Therefore, the cost associated with price changing can account for a considerable large portion of the profit and needs to be paid attention to (Chen et al., 2015). This price revision cost of the current solution might be acceptable in case of small grocery stores or convenience stores because there are less SKUs inside. However, the cost may increase significantly when it comes to bigger stores like supermarket, hypermarket, etc. Here, the amount of employee's cost will increase along with larger number of SKUs. The second drawback is the inconsistency in the determination of the risky batch. Each store employee or manager will have a different point of view when it comes to decision making. Some may determine based on the remaining shelf life and attach a 30% discount label if there is one day before the product expires. The other may make decision based on how many units are there in the soon-to-expired batch. Other combinations, for example how many batches is coming, the balance of other batches, is possible as well. The last drawback is the one-time discount. There is evidence from many dynamic pricing literatures that optimal dynamic pricing or multi-stage markdown pricing yield better results in terms of profitability, number of spoilages, etc. Within the scope of this thesis, it is assumed that the cost of price revision is significant and the optimal markdown pricing is profitable and can be adopted as a solution to the third drawback.

To sum up, current information system and set up in grocery stores do not allow for an effective and automatic dynamic pricing in the presence of multiple batches on shelf. In addition, new technologies to solve the problem cannot be adapted in near future, although they are already available in the market. Furthermore, the manual price revision results in a high cost, especially in case of big grocery stores with significant number of SKUs. As the current intermediate solution practicing by many grocery retailers contains several drawbacks, there is room for improvement. Finally, there is a need for a new proposed design which is based on the disadvantages of the third current solution. From now on, the name "current solution" will replace the "third current solution".

4.2 Objectives of the proposed solution

Before going to design a new solution, objectives of the proposed solution need to be created based on the advantages and disadvantages of the current solution from previous section. In below paragraph, objectives will be clearly defined.

Based on above discussion regarding the operational process, the advantages and disadvantages of the current solution, there is a need for a new design proposition to improve the current practice. The primary objective of the proposed solution is that it is capable to automatically identify risky on-shelf batches of each SKU. How risky a batch is can be determined by a given a forecast. The forecast can provide the probability that certain amount (units) of a specific batch of a SKU is going to be spoiled by the end of its shelf life. At the end of the design process, the proposed solution should be an implementable operational process which reveals SKU containing risky batches. As being discussed in section 1.2 in chapter 1, it is assumed that the proposed solution does not need to incorporate consumer package size, product substitution and cannibalization. The focus is only based on order quantity (replenishment quantity), beginning inventory of SKU when the order is replenished and the remaining shelf life.

4.3 Design and development of the proposed solution

This section presents how the proposed solution was created, developed and modified. The proposed solution is not only the application of statistical models, instead, it combines different approaches/processes which together provide a unified method to tackle product batch identification issue in dynamic pricing. In next steps, three common approaches for the proposed solution before the modelling in the first and second iterations will first be explained. Then different statistical models will be fitted to the generated data (Section 3.2.1 chapter 3), as well as, the assessment of the model fit will be conducted before generating spoilage forecasts. Finally, the forecasting model in the desgin from the second iteration will be integrated to a process with a third iteration for an ease of design implementation.

4.3.1 General approach

This general approach section aims to describe needed steps before a model can be applied to generate the forecast of spoiled quantity. The first important step is to identify all batches which are currently available on shelf. Figure 6 shows an example of identified batches based on the provided data. It is noted that it is impossible to conduct methods in this section with the generated raw data discussed in section 3.2.1 chapter 3. To do it, the raw data needs to be transformed which will be described in detail in the next section (4.3.2). By applying the algorithm in Figure 7, there is a difference between today date and replenishment date of batch 1, 2, 3 and 4. The magnitude of the difference are 8, 4, 3 and 1 days, respectively. Batch 1 is not on the shelf anymore because the difference of 8 days is greater than its shelf life (5 days). Batch 2, 3 and 4 are currently on the shelf because the difference are all less than 5 days. The remaining shelf life of batch 2, 3 and 4 are 1, 2 and 4 days, respectively.

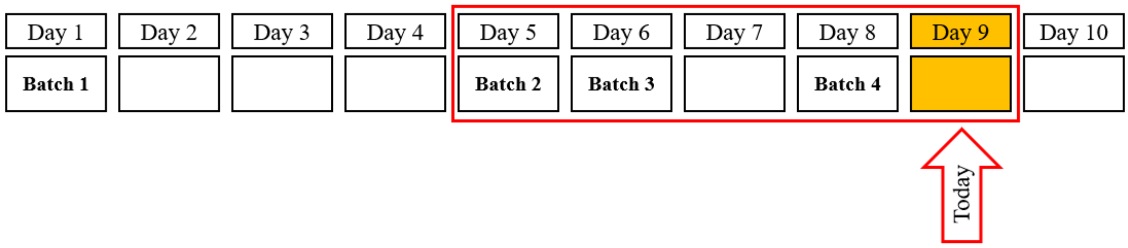

Figure 6. Illustration for on-shelf batches identification

$Algorithm\text{: } Available\ on-shelf\ batches\ identification$

$Set\ today = current\ date$

$\boldsymbol{for}\ each\ batch\ i\ in\ all\ batches\ \boldsymbol{do}$

$\quad \boldsymbol{if}\ today - replenishment\_date_i < shelf\_life_p$

$\quad \boldsymbol{then}\ provide\ information\ about\ batch_i$

$\quad \boldsymbol{else}\ next$

$\boldsymbol{end\ for}$

Figure 7. Algorithm to identify available on-shelf batches

After detecting available on-shelf batches, the algorithm queries the info from the data. Figure 8 show the layout and variables from each batch. In general, there are 6 variables, including: Product type (A, B, C and D), Batch number, Replenished date (When the batch is replenished on shelf), Expired date (When the batch will be discarded), Ordered batch quantity (Batch size) and Beginning inventory of the product on shelf when the batch is replenished (aggregate of all balance of batches).

Batch 2

Product	Batch	Replenished date	Expired date	Ordered batch quantity	Beginning inventory of product on shelf
A	2	5	9	48	17

Batch 3

Product	Batch	Replenished date	Expired date	Ordered batch quantity	Beginning inventory of product on shelf
A	3	6	10	24	23

Batch 4

Product	Batch	Replenished date	Expired date	Ordered batch quantity	Beginning inventory of product on shelf
A	4	8	12	72	9

Figure 8. Illustration for information of identified batches

Based on provided information of available batches, those variables will act as input into forecasting model which will be discussed in later sections. Finally, the proposed solution will generate the forecast on estimated number of spoiled quantities. In addition, it also provides the probability information, for example: the probability if spoiled quantity is greater than 10 units given product A with order batch quantity 36 and beginning inventory of 17.

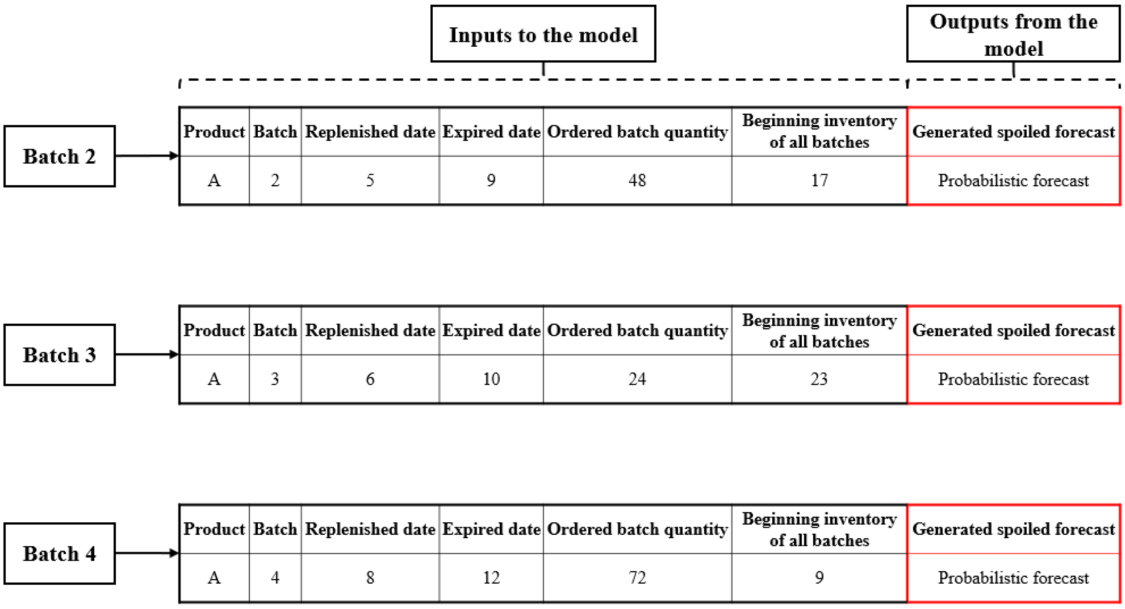

Figure 9. Illustration for inputs and outputs of the proposed solutions

4.3.2 Data preparation and transformation

In this section, a comprehensive and detailed process to prepare and transform the raw data provided by the expert as being discussed in section 3.2 of chapter 3 will be described. The ultimate aim of this process is to turn raw created data from SKU level into SKU and batch level. Below Figure 10 includes 5 steps. Next, each step will be further explained.

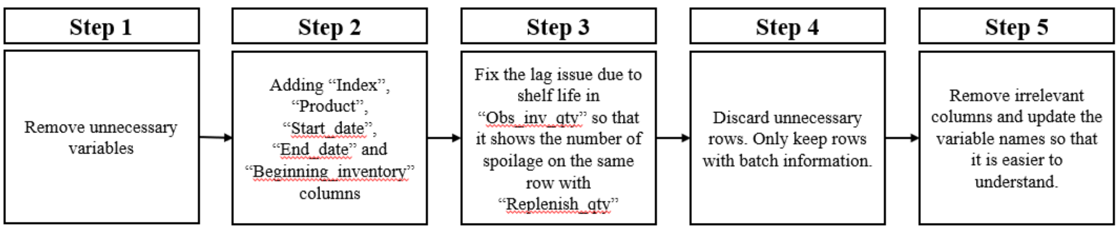

Figure 10. Data preparation and transformation for modeling process

The provided raw data from the expert contains 7 variables. In the first step, regarding the scope of this thesis, variables "Forecast", "Sales", "Order_qty" and "review_date" were discarded. The focus of the proposed solutions emphasizes on the modeling of the amount of spoilage based on replenishment quantity and beginning inventory. Therefore, the “Forecast” variable is not needed because it is simply a naive forecast with the same number for every rows. The removal of “Sales” variable is because it is impossible to know for certainty how many units of each batch for a product contribute to every daily sales number. In order to model the sales variable together with batches, assumptions regarding the allocation of sales on batch level based on consumer behavior needs to be made which is out of scope from this thesis. According to the variable “Order_qty”, it was discarded because of its similarity with “Replenish_qty” variable. Instead, “Replenish_qty” is “Order_qty” with a lag of 2 days and the rule is the same for all 4 products. That is why it is prerequisite to choose only one variable to avoid the effect of multicollinearity in the modeling step. Finally, the “review_date” is also unnecessary for the modeling because the interval between order is fixed.

Result from step 1

Inv_hand	Replenish_qty	Obs_inv_qty
23	0	0
11	0	0
57	54	0
46	0	0
30	0	9
54	30	0
19	0	24

Figure 11. Result from step 1 of data preparation and transformation for modeling process (Example from the first 7 rows in product A dataset)

In the second step, 5 columns were added to the table from step 1, including: “Index”, “Product”, “Start_date”, “End_Date” and “Beginning_inventory”. “Index” column acts as the date and is just simply an increment of 1 from the start 1 for every row. “Product” column is used to identify the type of product of a specific dataset and it has the same value for all rows in the dataset. “Start_Date” column has the same value and formula as “Index” column. “End_date” column was generated based on below formula:

$$\boldsymbol{End\_date_i = Start\_date_i + Shelf\_life_p} \quad (11)$$

(where $\text{Shelf\_life}_\text{p}$ means given shelf life (days) of product p)

"Beginning_inventory" column was created based on "Inv_hand" column through the formula: $Beginning\_inventory_i = Inv\_hand_{i-1}$. The reason "Beginning_inventory" variable was used, instead of "Inv_hand" variable, is that the ordered batch is replenished at the beginning of the day. Accordingly, it is logical and aligned to use the ending inventory of the previous day or the beginning inventory of current day.

Result from step 2

Index	Product	Start_date	End_date	Beginning_inventory	Inv_hand	Replenish_qty	Obs_inv_qty
1	A	1	5		23	0	0
2	A	2	6	23	11	0	0
3	A	3	7	11	57	54	0
4	A	4	8	57	46	0	0
5	A	5	9	46	30	0	9
6	A	6	10	30	54	30	0
7	A	7	11	54	19	0	24

Figure 12. Result from step 2 of data preparation and transformation for modeling process (Example from the first 7 rows in product A dataset)

At step 3, a readjusted column for "Obs_inv_qty" was created under the name "Spoiled_quantity". This new column is needed to align the amount of spoilage to the same row as "Replenish_qty", so that it is easier to fit the model in later steps. The formula adopted to create the new column is like: $\mathbf{Spoiled\_quantity_b = Obs\_inv\_qty_{End\_date_b}}$. The formula can be interpreted as the spoiled quantity of batch b is equal to the observed inventory quantity at the end date of batch b.

Result from step 3

Index	Product	Start_date	End_date	Beginning_inventory	Inv_hand	Replenish_qty	Obs_inv_qty	Spoiled_quantity
1	A	1	5		23	0	0	0
2	A	2	6	23	11	0	0	0
3	A	3	7	11	57	54	0	24
4	A	4	8	57	46	0	0	0
5	A	5	9	46	30	0	9	0
6	A	6	10	30	54	30	0	7
7	A	7	11	54	19	0	24	0

Figure 13. Result from step 3 of data preparation and transformation for modeling process (Example from the first 7 rows in product A dataset)

In step 4, all unnecessary rows with zero replenishment quantity were discarded from the dataset for each product. As can be seen from Figure 14, all rows inside red boxes were removed and only rows which contain batch information were kept for later modeling task.

Result from step 4

Index	Product	Start_date	End_date	Beginning_inventory	Inv_hand	Replenish_qty	Obs_inv_qty	Spoiled_quantity
1	A	1	5		23	0	0	0
2	A	2	6	23	11	0	0	0
3	A	3	7	11	57	54	0	24
4	A	4	8	57	46	0	0	0
5	A	5	9	46	30	0	9	0
6	A	6	10	30	54	30	0	7
7	A	7	11	54	19	0	24	0

Figure 14. Result from step 4 of data preparation and transformation for modeling process (Example from the first 7 rows in product A dataset)

In the last step (step 5), columns “Inv_hand” and “Obs_inv_qty” were removed. “Inv_hand” and “Obs_inv_qty” columns were replaced by “Beginning_inventory” and “Spoiled_quantity” columns, respectively. Finally, the header name of “Replenish_qty” column was changed to “Replenishment_quantity” for better clarity.

Result from step 5

Index	Product	Start_date	End_date	Beginning_inventory	Replenishment_quantity	Spoiled_quantity
1	A	3	7	13	48	16
2	A	6	10	21	30	1
3	A	9	13	2	66	21
4	A	12	16	29	36	8
5	A	15	19	9	60	26
6	A	18	22	36	30	11
7	A	21	25	11	54	27

Figure 15. Result from step 5 of data preparation and transformation for modeling process (Example from the first 7 rows in product A dataset)

At the end of the process, four cleaned and transformed datasets were created for each SKU or product. Figure 15 shows an example of product dataset after the preparation and transformation. Every row in the dataset represents batch level information. This highlights a transition from SKU level to SKU and batch level data.

4.3.3 Split of datasets and forecasting horizon

Before proceeding to the modelling task, prepared data from the previous section needs to be splitted in to training and test sets. This activity ensures that the comparison in the evaluation is objective. According to chapter 3, there are 4 datasets for each of product (A, B, C and D). Each product dataset contains 4-year data (1460 rows in total). The first 3-year data in each dataset was splitted and used as training set to fit the models. The rest of 1-year data was used as the test set. Table 6 shows a summary of number of rows there are in the training and test set. As can be seen from this table, the number of rows is not equal between products. It is understandable as the data used for modelling contains only rows which has replenishment quantity. In addition, the number of placed orders differs from product to product depending on whether the product has high or low volume and the level of MOQ.

Table 6. Summary of training and test dataset

Product	Total rows	Number of rows in training set	Number of rows in test set	Number of discarded rows
A	1460	363	120	977
B	1460	360	120	980
C	1460	270	88	1102
D	1460	155	50	1255

Regarding the forecasting horizon, long-term forecasts was created for every product batch. It means after fitting 4 models using two approaches to each product 3-year dataset, those models were then used to generate forecasts for 1-year data in the test set. Then the performance of two methods against each product type was compared in “Results” section.

4.3.4 First iteration

Figure 16 provides detailed design process of the proposed solution using Poisson regression approach in the 1st iteration. The design is based on the general design process adapted from (Peffers et al., 2007) as discussed in chapter 3. Because the identify problem and motivate steps were already discussed in section 4.1 and 4.2, the remaining design and development, demonstration and evaluation steps for the 1st iteration design process will be described and explained.

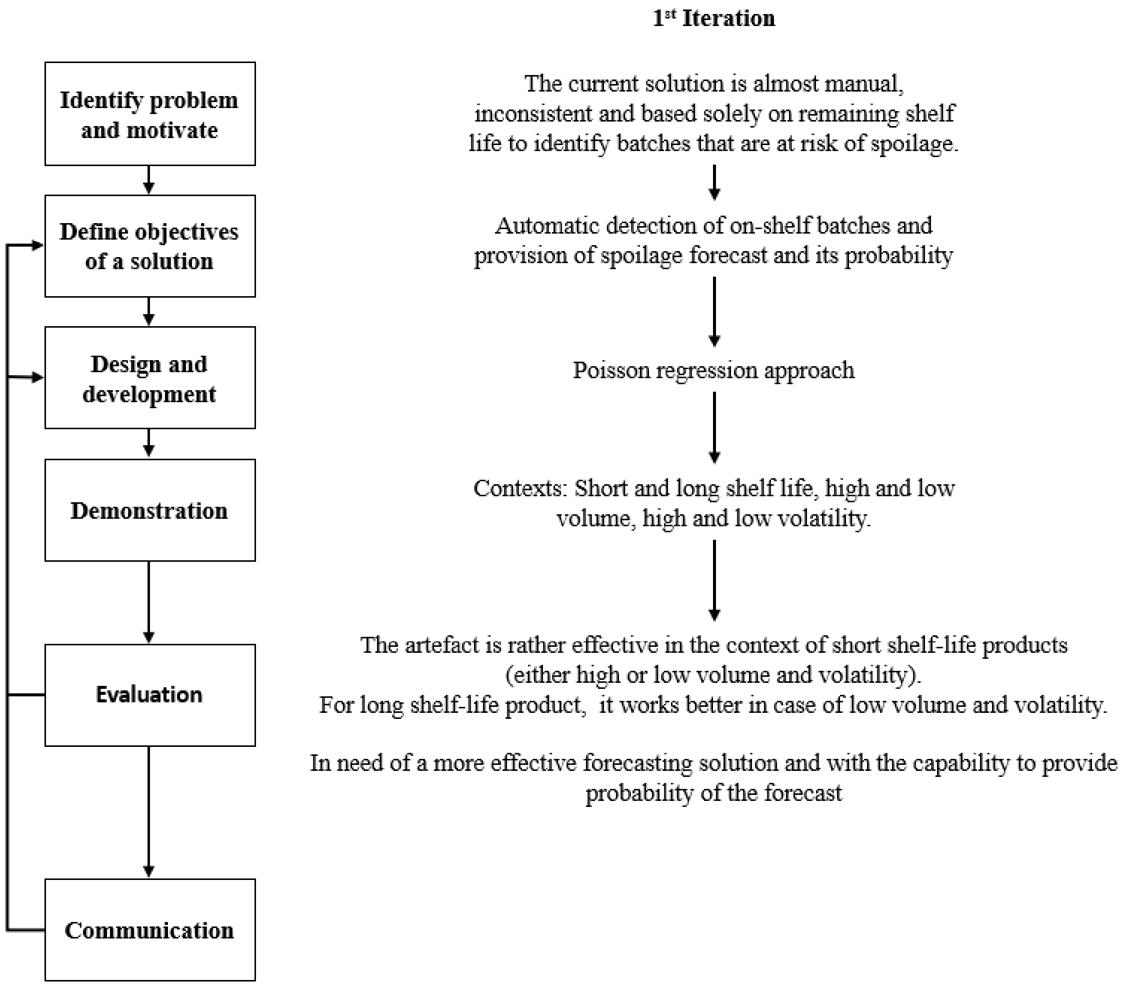

Figure 16. Detailed design science research process of 1st iteration

The proposed solution in the 1st iteration which is Poisson regression was implemented and engineered using "stats" package in R environment. It was tested with 4 products A, B, C and D which represents the 4 contexts: High volume/High volatility/Short shelf life, Low volume/Low volatility/Long shelf life, High volume/High volatility/Long shelf life and Low volume/Low volatility/Short shelf life. The applicable formula of the Poisson regression model is as following:

$$\boldsymbol{log(Spoiled\_quantity) = \beta_0 + \beta_1 * Beginning\_inventory + \beta_2 * Replenishment\_quantity)} \quad (12)$$

The reason for using natural logarithm in the response variable, Spoiled_quantity, is that it has count and non-negative value. After fitting the model and optimizing the coefficients, it is needed to exponent the formula for the interpretation. Below is the modified formula:

$$\boldsymbol{Spoiled\_quantity = e^{\beta_0+\beta_1*Beginning\_inventory+\beta_2*Replenishment\_quantity}} \quad (13)$$

Regarding product A, Figure 24 and Figure 25 show that the fitted model explained quite well the data with pseudo-R^2 equals nearly 70%. It can be interpreted that an increase of 1 unit in beginning inventory will lead to an increase of 1 unit in spoiled quantity. In addition, an increase of 1 unit in replenishment quantity will lead to an increase of 1.04 unit in spoiled quantity. For product B, Figure 26 and Figure 27 also shows a good fit with pseudo-R^2 equals to 68%. The model for product B shows that an increase of 1 unit in beginning inventory will lead to an increase of 0.97 unit in spoiled quantity and an increase of 1 unit in replenishment quantity will lead to an increase of 1.1 unit in spoiled quantity. According to product C (Figure 28 and Figure 29), the pseudo-R^2 of 28% shows that the model did not fit well with the data. The optimized coefficients can be interpreted as an increase of 1 unit in beginning inventory will lead to an increase of 1 unit in spoiled quantity and an increase of 1 unit in replenishment quantity will lead to an increase of 1.03 unit in spoiled quantity. Finally, the model summary result of product D (Figure 30 and Figure 31) again show a good fit with 67% pseudo-R^2. The resulted coefficients show that as an increase of 1 unit in beginning inventory will lead to an increase of 1 unit in spoiled quantity and an increase of 1 unit in replenishment quantity will lead to an increase of 1.11 unit in spoiled quantity.

After fitting the model to training data, it will then be used to make predictions of spoiled quantity on test data. The detailed result of prediction performance will be discussed in section 4.4. In addition to be able to generate the forecast, the design can also create a prediction interval (Figure 44, Figure 45, Figure 46 and Figure 47). These prediction intervals are confidence intervals with level of significance equals to 5%. In conclusion, the proposed solution in iteration 1 was able to provide an automatic forecast on spoiled quantity and it works well under the context of product A (High volume/High volatility/Short shelf life), product B (Low volume/Low volatility/Long shelf life) and product D (Low volume/Low volatility/Short shelf life). Although the design from iteration 1 can generate the prediction interval, it is simply a confidence interval which is based on the test dataset without prior information and is not a probabilistic statement. Thus, there is a need for a better performance solution, as well as, the capability to provide additional information regarding the probability of the forecast.

4.3.5 Second iteration

Based on identified drawbacks of iteration 1, an improved Poisson regression model with Bayesian methodology was implemented. Figure 17 depicts the transfer from 1st iteration to 2nd iteration from evaluation step. Next, the 2nd proposed solution will be discussed.

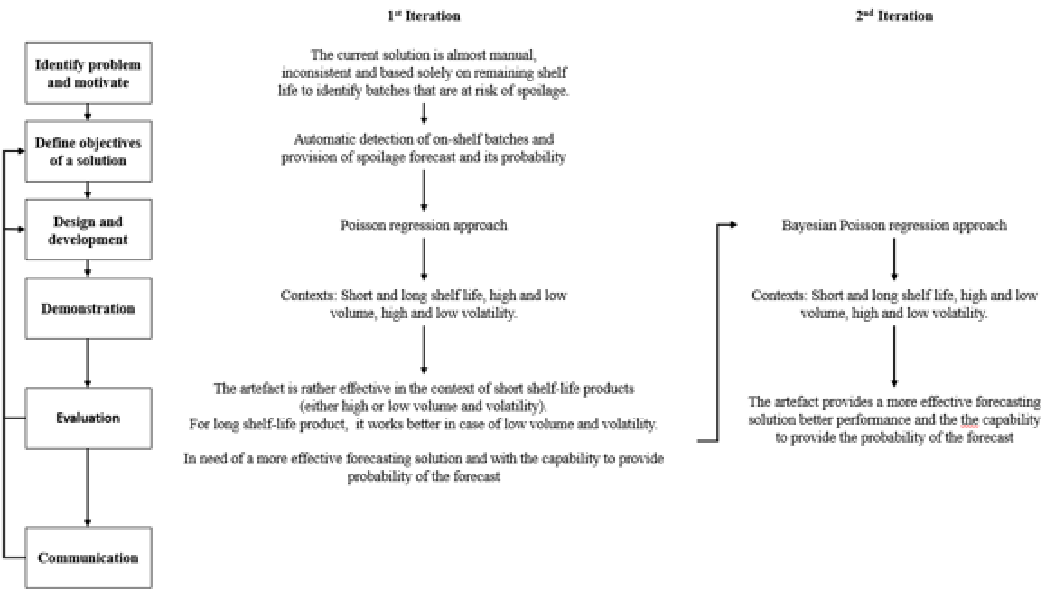

Figure 17. Detailed design science research process of 2nd iteration

Like the proposed solution in the 1st iteration, the Bayesian Poisson regression model was also implemented and engineered in R environment, but with a different package ("rstanarm"). Regarding the contexts and the function, both solutions are the same. The difference between two methods is also the difference between frequentist and Bayesian approach. The frequentist approach in regression (like Poisson regression) only provides a point estimate of the response variable. Whereas Bayesian approach generates a range of potential predicted values. Based on that range, one can get a point estimate in terms of min, max, mean, median, etc. Most importantly, it is possible to answer the question what the probability is if the predicted variable is less or greater than a specific value.

Back to Bayesian Poisson regression model fitting, the prior distribution for predictors and intercept were assumed to follow Normal distribution with mean equals to 0 and standard deviation equals to 3. In this thesis, there is no information about the prior that is why it has to be assumed. Regarding the simulation set up, the default of stan-glm function was adopted that is 1000 iterations and 4 chains (4000 samples in total). The random number generator seed was set to 12345.

Unlike Poisson regression which commonly uses R^2 or adjusted R^2 as metric to assess the goodness of fit, Bayesian Poisson regression normally use Rhat or elpd_loo for the assessment. As can be seen from summary and LOO estimate tables in Appendix 2, the model coefficients from all products have the same Rhat = 1 which mean that all models converged. In addition, the LOO estimate elpd_loo is less than the threshold 0.5 which states that the estimates converge quickly. Moreover, the posterior predictive Bayeisan Poisson regression model check visualizations in Appendix 2 which shows 2 histograms for the actuals and predictions confirm the for the fit because they are approximated. To sum up, the use of Bayesian regression model with assumed predefined parameters fit well with data from all products and can be used to generate the forecast in the test set.

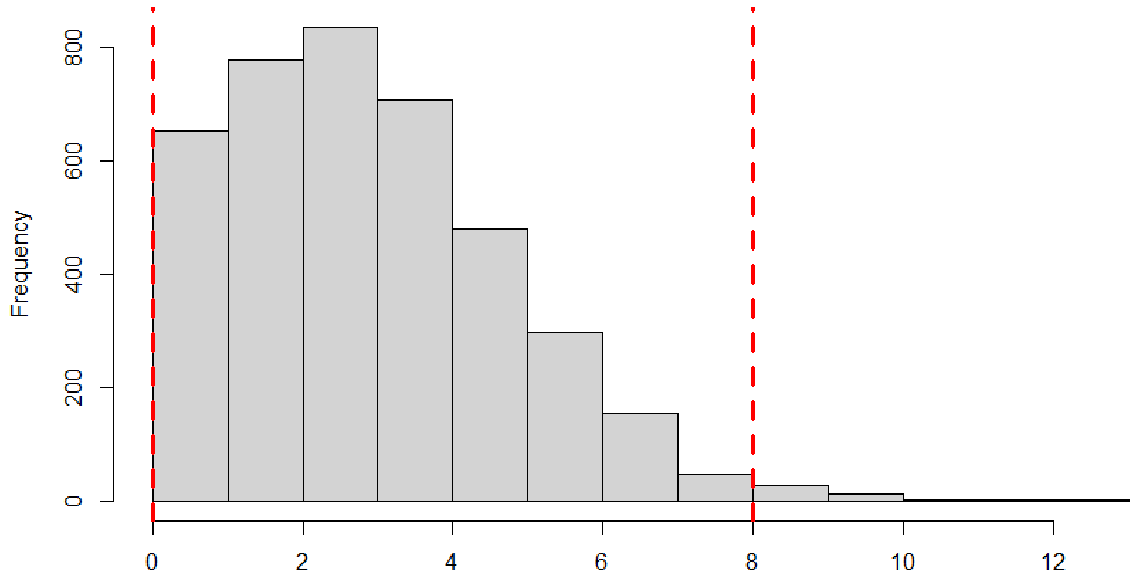

Figure 18. Potential predicted spoiled quantities and 95% interval of product D given information from a batch on shelf

After fitting the model to training data, it will then be used to make predictions of spoiled quantity on test data. The detailed result of prediction performance will be discussed in section 4.4. Unlike classic regression model, Bayesian regression model does not provide a point estimate. Instead, it is a list of possible outcomes (forecasts) given inputs from a batch. Based on that, the mean, median or other statistic (Q1, Q3, etc.) can be calculated.

In addition to be able to generate the forecast, the design can also generate a prediction credible interval (Figure 48, Figure 49, Figure 50 and Figure 51). Figure 18 shows the output of the model for product D given specific inputs of beginning inventory and replenishment quantity of a batch. The difference between the prediction (confidence) interval of the design in the iteration 1 and prediction (credible) interval of the design in the iteration 2 is mentioned in section 2.3.1 of literature review chapter. Reflect to operational management aspect, the users can not only get the forecast of spoiled quantity on average and prediction credible interval, but also be able to answer to the question what is the probability that certain units in a specific batch will be spoiled by the end of its shelf life given the order quantity and the beginning inventory of the product when the batch came. Based on that probability information, the users can make trade off whether to accept the risk or not.

4.3.6 Third iteration

Although the design in the second iteration provides high prediction accuracy on spoilage and the associated probability, it is difficult to implement it to real life situation. The reason is that the 2nd iteration design is simply a model which is able to provide forecast. In order to implement it to a grocery retail, there is a need for an end-to-end process.

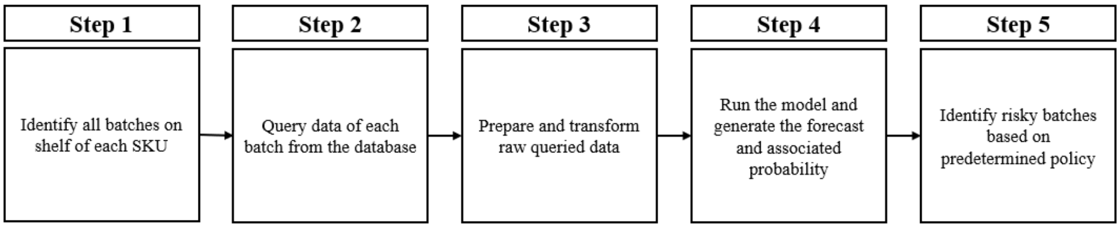

Figure 19. End-to-end operational process of the proposed solution

Figure 19 depicts an end-to-end operational process of the proposed solution. In the first step, all available batches which are currently placed on shelf needs to be detected by applying the algorithm described in section 4.3.1. After that, only relevant data (Order quantity, beginning inventory, replenishment date, etc.) for identified available batches of every SKU is queried from the grocery retailer's database or ERP (Enterprise Resource Planning) system in step 2. These two steps are very important in terms of running time of the proposed solution because it avoids querying the whole data of all batches of each SKU which is stored in the database. In addition, it also helps in running the model as not all batches need predictions. As discussed in section 4.3.2, the current raw data does not allow for the generation of spoilage forecasts at batch level. That is why it has to be transformed and prepared in step 3. Because the raw data is pseudo which mimics the real data at grocery retailers, it only needs to be transformed. In real life, other sub steps regarding data management may be required, for example: Appending, merging, splitting, cleaning, validation, etc. Then prepared and transformed datasets for every SKU will be feed into the Bayesian regression model. Due to the complexity of the Bayesian model, it takes time to run. The performance of the model will be discussed in section 4.4. While running, the Bayesian model will update the prior distribution and parameters given the new dataset. After that, a set of statistic (Min, Q1, average, median, Q3, max) and associated probability of the forecast will be given to every batch of each SKU.

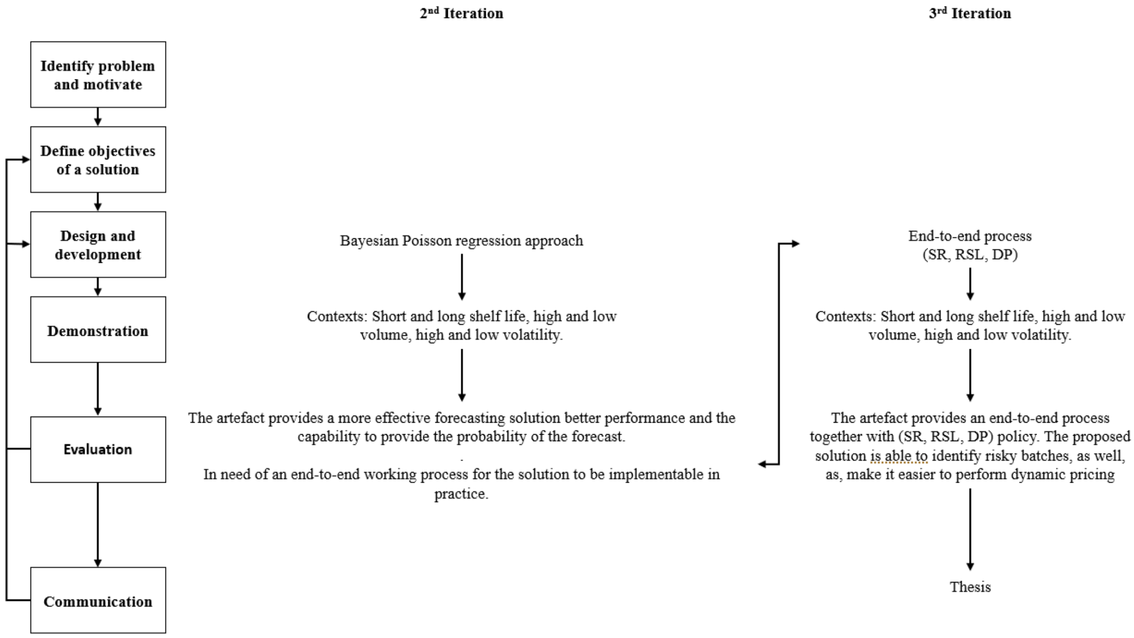

Figure 20. Detailed design science research process of 2nd iteration and 3rd iteration

All four steps in this end-to-end process have already been described so far in other previous subsections and only summarized in above paragraph. This is not something new for the third iteration. The key difference here is at the step 5. At the beginning of step 5, the 2nd iteration design provides us the forecast (including statistic and probability) and the remaining shelf life. The reason for not including "remaining shelf life" variable in the input into Bayesian Poisson regression model is that it does not add any value in for the model. Assuming a batch X of SKU A has shelf life of 5 days. The record of batch X feed into the model include order quantity and beginning inventory of SKU A when batch X is replenished. This record will be the same as every day passes within a shelf life of 5 days. The reason is that there is nothing differentiate between dates because it is impossible to know the batch balance in real life. It means the forecast from the 2nd iteration design and the remaining shelf life need to be connected somehow. One practical and feasible solution is to mimic inventory replenishment policy, for example (s, S) policy. (s, S) policy means inventory of a SKU needs to be reorder when its value reach the reorder point s and it needs to be ordered up to S. Regarding the new policy of this case, it should contain the remaining shelf life, discount percentage and a formula to combine forecast and probability. The proposed policy can be called as **(SR, RSL, DP)** where SR is spoilage rate, RSL means Remaining shelf life and DP stands for discount percentage). The spoilage rate (SR) is given by below formula:

$$\boldsymbol{SR} = \frac{\boldsymbol{Forecast\ given}\,\mathbf{Pr}(\boldsymbol{X} > \boldsymbol{Forecast}) \leq \boldsymbol{\alpha}}{\boldsymbol{Order\ quantity}} \tag{14}$$

(where X is a random variable represents the amount of spoilage and α is the risk factor)

The nominator of SR formula is the answer to the question "What is the predicted spoiled quantity if the probability (true spoilage is greater than the forecast) is less than or equal to the risk factor? The risk factor can be set by the grocery retailers, for example, 10%, 5%, etc. In general, the risk happens when the actual spoilage is greater than the forecast, so this risk factor needs to be controlled. This idea is similar to the significance level in statistics when performing the hypothesis testing. The lower the risk factor, the higher the predicted forecast, as well as the spoilage rate. This means operations manager has to place the discount earlier. The selection of the risk factor should come from the consideration of possible trade-off between giving discount too early and having too much spoilage. Identify the SKU which contains risky batches can be based on **(SR, RSL, DP)** policy, for example (0%, 5, 0), (10%, 3, 30%), (20%, 2, 50%) and (30%, 1, 70%). If batch X has spoilage rate between 0%-10% and remaining shelf life is less than 5 days, it is considered as no risk and should not be given any discount. If batch X has spoilage rate between 10%-20% and remaining shelf life is less than 3 days, it is considered as low risk and should be given 30% discount. If batch X has spoilage rate between 20%-30% and remaining shelf life is less than 2 days, it is considered as medium risk and should be given 50% discount. Finally, if batch X has spoilage rate greater than 30% and remaining shelf life is less than 1 day, it is considered as high risk and should be given 70% discount.

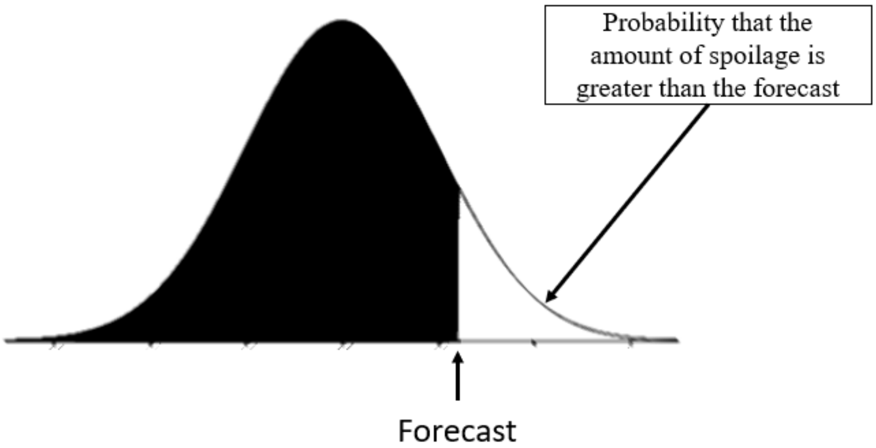

Figure 21. Illustration of spoilage rate in (SR, RSL, DP) policy

For the end-to-end process to be implemented in real life, grocery retailers should consider adopting a solution from specialized 3rd party service providers, for example RELEX, etc. These kind of supply chain optimization service providers are often specialized in providing optimal solutions for grocery retailers, for example: Forecasting, planning, replenishment, dynamic pricing, etc. The reason for the outsource is because every grocery retailer normally has huge number of SKUs (approx. 10,000 to 50,000 SKUs). In addition, price may differ from stores or locations, etc. Considering the combination of 4 dimensions (SKU, batch and store), the need for computational capability is significant because the data exponents very quickly. In addition, the set up and calibration of Bayesian Poisson regression model in the initial stage requires expertise in mathematics, statistics, machine learning and computer science. The 3rd service provider can develop and provide a software, an app or any kind of cloud solutions which could be installed on desktop computers, laptops and/or tablets. The daily operational process to identify risky batches and give discount can be performed by the operations manager in the morning. That person will use the laptop or tablet to run the installed software or use the web app provided by the 3rd party service provider. Then, the software will automatically compute the result following by the proposed end-to-end process. The outcome of the computation is a list of risky batches from all SKUs in the store with the risk categorization. After that, a discount percentage which is already set by the company will be applied to each risk category. By the end of the day, the store employees simply attach corresponding discount tag (30%, 50%, 70%, etc.) to risky batches which is clearly shown in the printed list.

4.4 Results and evaluation of the proposed solution

In this section, the results obtained from the proposed solution during the design process in previous sections is provided and discussed. Those are described in terms of comparison between proposed solutions at different iteration and the current solution. This section is divided into three sub sections corresponding to three criteria, including: Forecast accuracy and bias, computational complexity and usability. This section ends by giving an overall evaluation of the proposed solution as an operational process.

4.4.1 Forecast accuracy and bias

In this sub section, the results of forecasting spoilage obtained from the proposed solution in iteration 2 and 3 are compared to the one in iteration 1. It is not possible to compare with the current solution as the information is not available. Table 7, Table 8, Table 9 and Table 10 show the summary of prediction performance of 2 forecasting approach using 3 criteria for forecast accuracy and bias as discussed in section 2.4. As can be seen from the tables, Bayesian Poisson regression forecasting approach always performs better (with all products) in terms of forecasting accuracy, as compared to, Poisson regression forecasting approach. This results from much lower RMSE and MAE. Within 4 products, Bayesian approach perform best at product A followed by product B with RMSE % difference -69.08% and -52.98%, respectively. It can be concluded that Bayesian approach works well with short shelf-life data, no matter high or low volume. According to long shelf-life products (product C and D), Bayesian approach performs better when the volume is high, but the difference with product C (low volume) is closed (-44.90% vs -38.39%).

According to the measure of forecast bias (ME), the Poisson regression model has the tendency to over forecast. Especially, the positive bias is strong at high volume and short shelf-life product (product A). On the other hand, the Bayesian Poisson regression model has slight tendency to under forecast, except for low volume and short shelf-life product (product B). However, the bias in Bayesian Poisson regression model is not significant as ME measure is very close to 0.

4.4.2 Computational complexity

The computational complexity is illustrated using the computational times. The more computational times, the more complexity the proposed solution is. In this section, only the time from prepare and transform raw data to provide forecast is considered. In other words, only steps related to the modelling part in the design will be measure. In total, there are three steps from input data to generated forecast, including: data preparation and transformation, fitting models and generating forecasts. Because the codes and algorithms were only developed during "Fitting models" and "Generating forecasts" steps (Figure 22), computational times were only measured at each of the steps. After that, the sum of computational times at those steps were calculated. The comparison of the result will be discussed next.

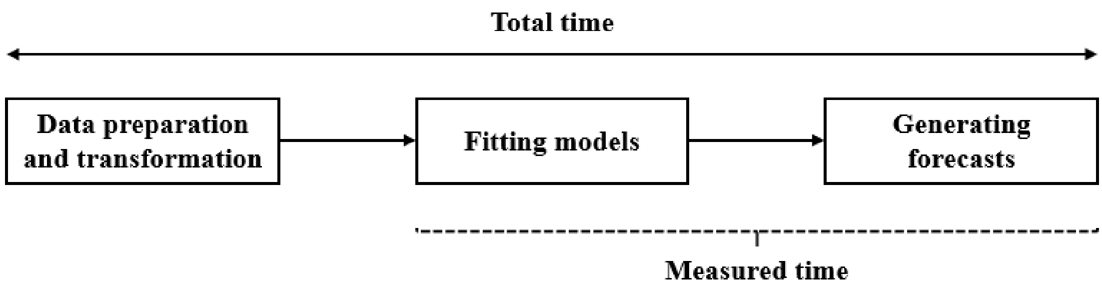

Figure 22. Measured point for computational complexity

All models and algorithms were developed and implemented in the development environment RStudio 1.4.1717 with R version 4.1.0. All computational experiments were run in gaming laptop Dell Alienware 15 R2 with processor Intel Core i7-6700HQ (8 CPUs), 2.6 GHz and 8 GB RAM.

Figure 23 depicts the comparison of total computational times between the modelling part of the proposed solution for long term forecasts at iteration 1 and 2 (the modelling part of iteration 2 and 3 are the same). Detailed measurements at fitting models and generating forecasts steps are given in Table 11 Appendix D. As can be seen from Figure 23, there are differences in computational times between approaches and product types. With the proposed solution using Poisson regression, the time taken to fit the model and generate forecasts decreases gradually from product A to product C with exception for product D which has higher time than product C. The reason for this decrease is perhaps due to the difference in number of data points in training and testing sets. According to the second proposed solution using Bayesian regression model, there is a clear distinction in computational times between high and volume products given the same volatility and shelf life (Product A vs B and product C vs D). By comparing two proposed modelling approach, it is easy to see that the Bayesian approach has much more time intensity than the non-Bayesian counterpart with minimum ratio of 210 in Product D and maximum ratio of 1440 in product C (Table 11, Appendix D). In general, the computational times of the proposed solution are expected given its complexity, as compared to the one in 1st iteration. As the computation was conducted on the laptop, the result must be improved when implemented at industry-grade servers in reality.

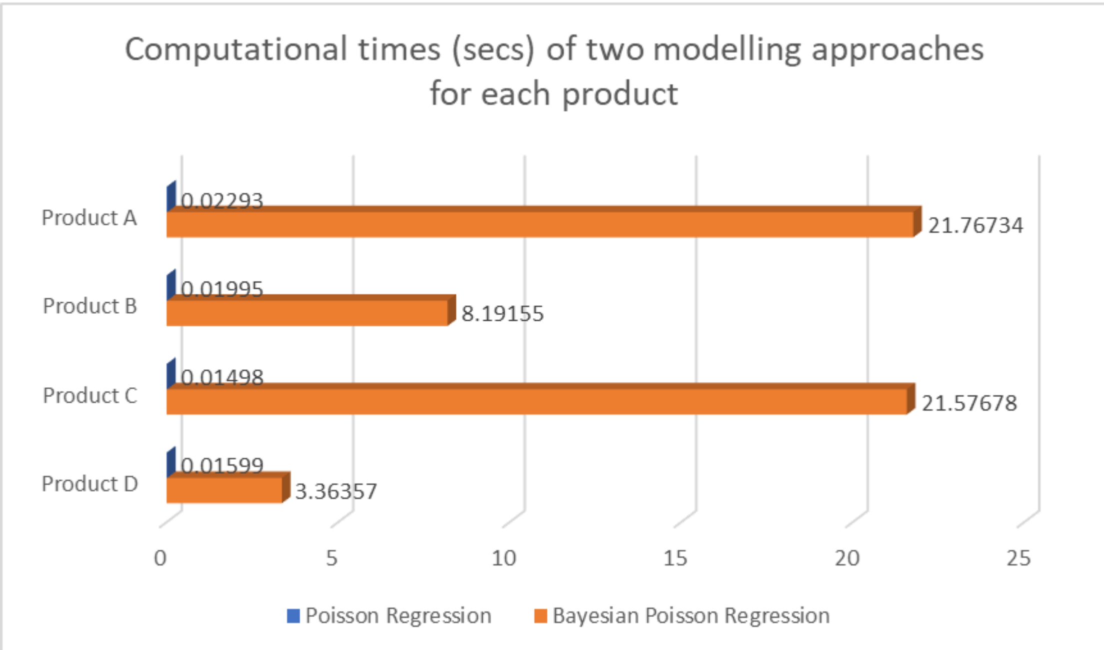

Figure 23. Computational times of two approaches for each product

4.4.3 Usability

The proposed solution in the 3rd iteration is not fully automated without the use of the 3rd party service provider. In the demonstration part of this thesis, only model fitting and forecasts generation step (step 4 in end-to-end process) was automated. The batch data query step (step 2 in end-to-end process) and data preparation and transformation step (step 3 in end-to-end process) can be easily automized. With the development of data pipeline, raw data from database of grocery retailers is queried and input into the proposed model which can be deployed in RStudio or on cloud to generate real time forecasts. The first step to identify available on-shelf batches for every SKU can also be done automatically using the proposed algorithm is section 4.3.1. The last step (step 5) to identify risky batches can only be automized after grocery retailers set the rule for (SR, RSL, DP) policy. Then activities to attach discount label to identified risky batch is totally manual. However, this further step is out of the scope of this thesis. In general, the proposed solution together with the participation of 3rd party service provider can provides benefits for end users in terms of an automatic solution, as compared to totally manual current solution.

In addition to automation perspective, the proposed solution also enhances the transparency and consistency. Although, the current manual solution is simple to understand, easy to implement and gives more freedom to operation managers than the proposed solution, it poses the risk of inconsistency and transparency. Due to the high level of user interaction involvement with various personalities, the decision to identify risky batches are different from person to person which lead to the inconsistency. In addition, how the decision is made is sometimes unclear while asking or interviewing the users which means lack of transparency.

In conclusion, in term of usability, the proposed solution is able to provide a partial automated solution with better transparency and consistency in comparison to the current manual solution.

4.4.4 Overall evaluation

The proposed solution in the form of an operational process has shown the potential in identifying risky batches which are at risk of spoilage. With generated data which mimics real life situation, the proposed solution works well in generating the forecast of spoiled quantity given the replenishment quantity (order quantity) of the batch and the beginning inventory of the SKU with very good forecasting accuracy low tendency of bias. Unfortunately, the proposed solution cannot be compared with the current solution regarding the forecasting accuracy and bias due to lack of real-life data. In terms of computational complexity, the proposed solution takes quite a lot of time to create the model and generate the forecast, especially with high volume product. It is noted that the measured time is only applied for modelling part. Other parts and the whole end-to-end process needs to be assessed in further study. Regarding the usability criteria, the end-to-end process of the proposed solution can be fully automized although only modelling part of it is able to provide the forecast automatically in this thesis. Apart from strong capability in making the forecast, the proposed solution provides a greater level of transparency and consistency as the output from the process is printed list which highlights risky batches of every SKU. The list can be updated daily as well. No matter the difference in products, batches, stores, employees, etc. the outcome from the proposed solution is extremely consistent and transparent. With reference to the application of dynamic pricing, it is easy to apply, at least with multi-stage markdown pricing as discussed in section 4.3.6. There is only one difficulty that is how to set up (SR, RSL, DP) rule in the beginning. This requires a collaboration between grocery retailers and 3rd party service provider.

5. Discussion

This section includes three subsections, namely: Contribution, practical implications and future research. Contribution subsection summarizes the proposed solution and describes its contribution to the current solution. In practical implication sub section, the benefit of the proposed solution in real life context will be discussed. Finally, the future research will provide research direction to the current proposed solution and its alternatives.

5.1 Contribution

In this thesis, an operational process to automatically identify on-shelf batches of perishable products which are at risk of spoilage in the context of grocery retailers was designed. This process helps to address existing drawbacks of the current solution. The proposed solution contributes to dynamic pricing and product identification research area by adopting Bayesian Poisson regression modeling technique in combination to other support processes to make feasible and implementable in real life.

The proposed solution is a 5-step operational process, including: Identify all available on-shelf batches for every SKU, query relevant data of each batch from the database, prepare and transform raw queried data, run the prediction model and generate probabilistic forecast and identify risky batches based on predetermined policy. Although the use of Bayesian methodology is widely adopted in many fields, there is very little literatures apply it in the context of product identification. The model used for generating spoilage forecast is called Bayesian Poisson regression with replenishment quantity and beginning inventory as regressors. The use of Poisson regression is because the generated data receives count number (units). There are also other methods to deal with count data, but Poisson regression is seen as classic and popular. The use of Bayesian approach is first due to its capability to provide forecast together with probabilistic statement. Secondly, it allows for a continuous update given initial belief (prior information). In order words, whenever a batch is discarded at the end of the shelf life, the information about amount of spoilage acts as new data will update current belief. Finally, it may allow for further involvement of store managers and employees when developing the solution as Bayesian methodology requires initial estimate about variables. Regarding dynamic pricing, step 5 in the operational process introduces a new policy which is called (SR, RSL, DP) policy. This structure of the policy helps to guide operations manager for a better discount/markdown pricing. In comparison to the current solution, the store managers and employees no longer need to perform the manual checking and determine for discount percentage. Store employees simply attach discount percentage label to the correct batches given by the operational process.

With generated data, the proposed solution has proven good performance when it comes to forecasting accuracy and bias. The required input data to the process is popular and can be retrieved easily. Other algorithm to detect batches is also simple. The only obstacle for the implementation is the persuasion for adoption of Bayesian regression model which has perform quite slow as the moment (~26 secs to fit the model and generate forecast for 1 SKU). However, this operational process can be seen as the first step into the identification of product batch and it can be further improved.

5.2 Practical implications

As e-commerce giants is expanding to grocery industry with numerous competitive advantages, traditional grocery retailers need to be more innovative, in order to, be survived. One of the key strengths of e-commerce companies is the ability to change the price easily and in real time. That is why dynamic pricing at e-commerce sector is widely adopted. On the contrary, the adoption of dynamic pricing in retail industry happens very slowly due to many barriers, for example changing the price required labors, set up of the information system is not capable to support, etc.

Although the proposed solution in this thesis is tested using pseudo data, it can be a starting point for grocery retailers to further improve from it. Thinking about the implementation of the proposed solution to current grocery retailers, the current proposed solution contains both pros and cons. Regarding the advantages, the proposed solution is actually an operational process and just not simply a statistical model which can be seen as black box in the eyes of store managers or employees. All the required data acts as input into the process must be available in any grocery stores' information system. By the end of the day, an ideal result from the process is that the operations manager goes to the store in the morning, opens his laptop to check which batches of what SKUs needs be discount and at what percentage. Then he/she will plan the job, print the list of risky batches together with discount percentage label and send it to every store employee. The task now becomes very simple as the store employee just need to attach the discount label one by one followed by the order in the list.

Disadvantages may arise from the prediction model and the retention to adopt it could be anticipated. As described in section 4.1, current practice in grocery retailers give much freedom for store/operations manager to make decision on which batch needs to be discount and what is the magnitude of it. The appearance of a black box which only give the output without clear and simple explanation can make them confused and avoid using it. To address this problem, it is crucial to early involve store managers and other employees in the development of such system. As all Bayesian regression models, regardless of distribution family, the initial step is to specify the prior which serves as the belief on certain variable. Here, the experience of store managers and employees can be utilized to provide a more educated initial guess. Another room for such involvement is with perishable products which does not have barcode, for example vegetables, bread, etc. In this case, the proposed solution cannot be conducted and it needs to be redesigned to incorporate the input data from visual checks of store employees.

5.3 Future research

This section is divided into three parts. The first part includes recommendation for further improving the current proposed solution. The second part looks at different alternatives to the current proposed solution. In the last part, a totally new perspective related supply chain will be discussed.

Regarding the current proposed solution, the spoilage prediction model using Bayesian Poisson regression can be improved by trying and testing other distribution family, for example zero-inflated Poisson distribution, zero-truncated Poisson distribution, negative binomial distribution, etc. It is noted that only the distribution family in the regression model will be changed. The Bayesian methodology adoption is still crucial. It is also beneficial if the proposed solution can be tested with real-life data and compared with the current practice through feasibility studies. If such studies can also include the cost of price revision comparison, it will help to validate the proposed solution. In addition, the current Bayesian Poisson regression model can be modified to incorporate other variables in current generated data like sales, current date, etc. Such variables, especially sales can be modelled as another regression model with lags. The idea is similar to dynamic regression modeling. Other assumption in this thesis like consumer pack size and substitutability are worth investigated. According to the step 5 in the operational process, the example described in section 4.3.6 of invented (SR, RSL, DP) is simply heuristics. It would be very interesting if an optimal solution could be found.

As discussed in the beginning, the perfect solution to this product batch identification is to adopt a more advanced product identification like RFID, QR, TTI, etc. These types of code can store more information than just the product itself which can help to differentiate product batches based on order date, delivery date or replenishment date, etc. As the variable cost of each RFID tag is decreasing continuously, the adoption can soon to be appeared to the market. Another intermediate method using technology is to improve current barcode set up to store more information. Grocery retailers can use another traditional barcode attach to the perishable products to store, for example order quantity or delivery date. Then using a specialized scanner to integrate the scanned codes of two tags into one. This solution is not something new, but it is already available on the market. One of the greatest benefits of apply technology is that it allows for tracking to the lowest granular (item level).

Finally, another view for future research is from the perspective of supply chain. In most of articles regarding dynamic pricing and product identification, the main context is on shelf perishable products at grocery stores and consumers. What if the same problem occurs at further upstream level, for example, distribution level. Does the current proposed solution, other current practice at retailers and methods in literatures still work?

6. Conclusion

In this thesis, the focus is based on perishable products at grocery retail industry. The thesis begins by identifying a research gap in current dynamic pricing together with product identification literatures which mainly focus on SKU level of perishable products. Therefore, there is a need of more research of dynamic pricing and product identification in the context of perishable products at batch level of SKUs. The proposed solution is an operational process that aims to automatically identify risky perishable product batches which are at risk of spoilage. It helps to address the current problem of consumer purchasing's attitude toward multiple batches on shelf with different remaining shelf life at grocery retail industry. By identifying correct risky batches, an effective dynamic pricing can be allowed and implemented in practice. Next, two objectives of this thesis which is presented in the first chapter will be revisited.

- Objective 1: Developing an automatic or partial automatic solution to identify perishable-product batches which are at risk of spoilage so that optimal dynamic pricing can be applied more effectively.

In the form of a 5-step operational process, the proposed solution in this thesis manages to identify and recommend perishable-product batches which are at risk of spoilage. Based on that, operations manager is able to determine the discount percentage and store employees can simply attach discount label based on a predefined list of SKUs which contain risky batches. Among 5-step of the operational process, only the data preparation and transformation step (Step 3) and Bayesian Poisson regression model fitting and generating forecasts (Step 4) can automatically perform the task with evidence from demonstration in chapter 4. The rest of the process with 3 remaining steps is developed with provided algorithm, detail description and explanation to identify current available batches on shelf for every SKU, query relevant data for those batches and generate a list of risky batches with the help of invented (SR, RSL, DP) policy. These 3 steps can be easily automated by 3rd party service providers such as RELEX, etc.

- Objective 2: Evaluating the feasibility and practicality in terms of implementation of the proposed solution to the context of grocery retail and perishable products in real life and the usefulness of it with regard to the helping the adoption of dynamic pricing.

Based on the performance measurement results and overall evaluation of the proposed solution, the 5-step operational process performs well with generated data from the expert in terms of spoilage forecasting accuracy and low tendency of bias. In terms of computational complexity, the proposed solution achieves the goal with considerable time to create the model and generate forecast as compared to the other simple methods. However, it can be fully automated in practice which helps to reduce a lot of user interactions as current solution. In addition, the proposed solution also provides a greater level of transparency and consistency in the identification of risky batches. Regarding dynamic pricing, the proposed process especially makes markdown pricing become more effective by targeting the discount to the right batch so that it could be cleared before expiration. The only obstacle here is how to set up the rule for (SR, RSL, DP) in the beginning. Despite potential benefits, this proposed solution still need to be further implemented and tested in real life for validation.

In conclusion, the result from this thesis can be utilized by grocery retail industry to address current facing challenges with regards to consumer purchasing's attitude towards mixing perishable batches and improve current manual solution. According to academic research, it also encourages for further future research to the context of dynamic pricing at batch level of perishable products at grocery retailers. Finally, the thesis may serve as a guideline for further development in the field of automation and optimization with the application to reality.

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Appendix

Appendix A. Model fit assessment for Poisson regression model

```
Call:
glm(formula = Spoiled_quantity ~ Beginning_inventory + Replenishment_quantity,
    family = "poisson", data = Product_A_Train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.4731  -0.8265   0.0493   0.5970   2.7230

Coefficients:
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)            0.707102   0.267075   2.648  0.00811 **
Beginning_inventory    0.001213   0.003863   0.314  0.75347
Replenishment_quantity 0.043388   0.004288  10.119  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 885.14  on 362  degrees of freedom
Residual deviance: 458.43  on 360  degrees of freedom
AIC: 2101.4

Number of Fisher Scoring iterations: 4
```

Figure 24. Summary of Poisson regression model for product A

```
MODEL INFO:
Observations: 363
Dependent Variable: Spoiled_quantity
Type: Generalized linear model
  Family: poisson
  Link function: log

MODEL FIT:
χ²(2) = 426.71, p = 0.00
Pseudo-R² (Cragg-Uhler) = 0.69
Pseudo-R² (McFadden) = 0.17
AIC = 2101.41, BIC = 2113.10

Standard errors: MLE
----------------------------------------------------------------------
                              exp(Est.)   2.5%   97.5%   z val.      p
---------------------------- ----------- ------ ------- -------- ------
(Intercept)                        2.03   1.20    3.42     2.65   0.01
Beginning_inventory                1.00   0.99    1.01     0.31   0.75
Replenishment_quantity             1.04   1.04    1.05    10.12   0.00
----------------------------------------------------------------------
```

Figure 25. Figure. Summary of Poisson regression model for product A (Exponential coefficients)

```
Call:
glm(formula = Spoiled_quantity ~ Beginning_inventory + Replenishment_quantity,
    family = "poisson", data = Product_B_Train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.2437  -0.7040   0.0400   0.6352   2.1537

Coefficients:
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)             0.69425    0.21945   3.164  0.00156 **
Beginning_inventory    -0.03557    0.01324  -2.686  0.00722 **
Replenishment_quantity  0.09532    0.01242   7.676 1.64e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 809.70  on 359  degrees of freedom
Residual deviance: 404.73  on 357  degrees of freedom
AIC: 1560.1

Number of Fisher Scoring iterations: 5
```

Figure 26. Summary of Poisson regression model for product B

```
MODEL INFO:
Observations: 360
Dependent Variable: Spoiled_quantity
Type: Generalized linear model
  Family: poisson
  Link function: log

MODEL FIT:
χ²(2) = 404.97, p = 0.00
Pseudo-R² (Cragg-Uhler) = 0.68
Pseudo-R² (McFadden) = 0.21
AIC = 1560.10, BIC = 1571.76

Standard errors: MLE
--------------------------------------------------------------------
                              exp(Est.)   2.5%   97.5%   z val.     p
---------------------------- ----------- ------ ------- -------- ------
(Intercept)                        2.00   1.30    3.08     3.16   0.00
Beginning_inventory                0.97   0.94    0.99    -2.69   0.01
Replenishment_quantity             1.10   1.07    1.13     7.68   0.00
--------------------------------------------------------------------
```

Figure 27. Summary of Poisson regression model for product B (Exponential coefficients)

```
Call:
glm(formula = Spoiled_quantity ~ Beginning_inventory + Replenishment_quantity,
    family = "poisson", data = Product_C_Train)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.88191  -0.83732  -0.02479   0.70514   2.81363

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)            0.1552414  0.5848994   0.265    0.791
Beginning_inventory    0.0004263  0.0064917   0.066    0.948
Replenishment_quantity 0.0297766  0.0068459   4.350 1.36e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 427.92  on 269  degrees of freedom
Residual deviance: 340.44  on 267  degrees of freedom
AIC: 1290.7

Number of Fisher Scoring iterations: 4
```

Figure 28. Summary of Poisson regression model for product C

```
MODEL INFO:
Observations: 270
Dependent Variable: Spoiled_quantity
Type: Generalized linear model
  Family: poisson
  Link function: log

MODEL FIT:
χ²(2) = 87.48, p = 0.00
Pseudo-R² (Cragg-Uhler) = 0.28
Pseudo-R² (McFadden) = 0.06
AIC = 1290.69, BIC = 1301.48

Standard errors: MLE
-----------------------------------------------------------------------
                               exp(Est.)    2.5%    97.5%    z val.      p
---------------------------- ----------- ------ -------- -------- ------
(Intercept)                         1.17   0.37     3.68     0.27   0.79
Beginning_inventory                 1.00   0.99     1.01     0.07   0.95
Replenishment_quantity              1.03   1.02     1.04     4.35   0.00
-----------------------------------------------------------------------
```

Figure 29. Summary of Poisson regression model for product C (Exponential coefficients)

```
Call:
glm(formula = Spoiled_quantity ~ Beginning_inventory + Replenishment_quantity,
    family = "poisson", data = Product_D_Train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6022  -1.4296  -0.1977   0.7690   3.7576

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)            -0.588297   0.298733  -1.969   0.0489 *
Beginning_inventory     0.001118   0.015309   0.073   0.9418
Replenishment_quantity  0.099879   0.011649   8.574   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 467.83  on 154  degrees of freedom
Residual deviance: 299.23  on 152  degrees of freedom
AIC: 707.36

Number of Fisher Scoring iterations: 5
```

Figure 30. Summary of Poisson regression model for product D

```
MODEL INFO:
Observations: 155
Dependent Variable: Spoiled_quantity
Type: Generalized linear model
  Family: poisson
  Link function: log

MODEL FIT:
χ²(2) = 168.59, p = 0.00
Pseudo-R² (Cragg-Uhler) = 0.67
Pseudo-R² (McFadden) = 0.19
AIC = 707.36, BIC = 716.49

Standard errors: MLE
------------------------------------------------------------------------
                                 exp(Est.)    2.5%   97.5%   z val.      p
---------------------------- ----------- ------ -------- --------- ------
(Intercept)                         0.56    0.31    1.00    -1.97   0.05
Beginning_inventory                 1.00    0.97    1.03     0.07   0.94
Replenishment_quantity              1.11    1.08    1.13     8.57   0.00
------------------------------------------------------------------------
```

Figure 31. Summary of Poisson regression model for product D (Exponential coefficients)

Appendix B. Model fit assessment for Bayesian Poisson regression model

```
Model Info:
 function:     stan_glm
 family:       poisson [log]
 formula:      Spoiled_quantity ~ Beginning_inventory + Replenishment_quantity
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 363
 predictors:   3

Estimates:
                       mean   sd   10%   50%   90%
(Intercept)           0.7    0.3  0.3   0.7   1.0
Beginning_inventory   0.0    0.0  0.0   0.0   0.0
Replenishment_quantity 0.0    0.0  0.0   0.0   0.0

Fit Diagnostics:
           mean   sd   10%   50%   90%
mean_PPD 15.8    0.3 15.4  15.8  16.2

The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for details see help('summary.stanreg')).

MCMC diagnostics
                       mcse Rhat n_eff
(Intercept)            0.0  1.0  1196
Beginning_inventory    0.0  1.0  1304
Replenishment_quantity 0.0  1.0  1215
mean_PPD               0.0  1.0  2733
log-posterior          0.0  1.0  1385

For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence Rhat=1).
```

Figure 32. Summary of Bayesian Poisson regression model for product A

```
Computed from 4000 by 363 log-likelihood matrix

         Estimate   SE
elpd_loo  -1051.1 17.1
p_loo         3.7  0.5
looic      2102.2 34.1
------
Monte Carlo SE of elpd_loo is 0.0.

All Pareto k estimates are good (k < 0.5).
See help('pareto-k-diagnostic') for details.
```

Figure 33. LOO estimate of product A

```
Model Info:
 function:     stan_glm
 family:       poisson [log]
 formula:      Spoiled_quantity ~ Beginning_inventory + Replenishment_quantity
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 360
 predictors:   3

Estimates:
                         mean   sd   10%   50%   90%
(Intercept)            0.7    0.2  0.4   0.7   1.0
Beginning_inventory    0.0    0.0 -0.1   0.0   0.0
Replenishment_quantity 0.1    0.0  0.1   0.1   0.1

Fit Diagnostics:
           mean   sd   10%   50%   90%
mean_PPD 5.3    0.2  5.1   5.3   5.5

The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for details see help('summary.stanreg')).

MCMC diagnostics
                       mcse Rhat n_eff
(Intercept)            0.0  1.0  1705
Beginning_inventory    0.0  1.0  1792
Replenishment_quantity 0.0  1.0  1761
mean_PPD               0.0  1.0  2812
log-posterior          0.0  1.0  1215

For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence Rhat=1).
```

Figure 34. Summary of Bayesian Poisson regression model for product B

```
Computed from 4000 by 360 log-likelihood matrix

         Estimate   SE
elpd_loo   -780.0 11.5
p_loo         2.8  0.2
looic      1560.1 23.1
------
Monte Carlo SE of elpd_loo is 0.0.

All Pareto k estimates are good (k < 0.5).
See help('pareto-k-diagnostic') for details.
```

Figure 35. LOO estimate of product B

```
Model Info:
 function:     stan_glm
 family:       poisson [log]
 formula:      Spoiled_quantity ~ Beginning_inventory + Replenishment_quantity
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 270
 predictors:   3

Estimates:
                         mean   sd   10%   50%   90%
(Intercept)             0.1    0.6 -0.6   0.1   0.9
Beginning_inventory     0.0    0.0  0.0   0.0   0.0
Replenishment_quantity  0.0    0.0  0.0   0.0   0.0

Fit Diagnostics:
           mean   sd   10%   50%   90%
mean_PPD 5.9    0.2  5.7   5.9   6.2

The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for details see help('summary.stanreg')).

MCMC diagnostics
                       mcse Rhat n_eff
(Intercept)            0.0  1.0  1605
Beginning_inventory    0.0  1.0  1644
Replenishment_quantity 0.0  1.0  1657
mean_PPD               0.0  1.0  2645
log-posterior          0.0  1.0  1087

For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence Rhat=1).
```

Figure 36. Summary of Bayesian Poisson regression model for product C

```
Computed from 4000 by 270 log-likelihood matrix

         Estimate   SE
elpd_loo   -645.6 13.4
p_loo         3.6  0.6
looic      1291.2 26.7
------
Monte Carlo SE of elpd_loo is 0.0.

All Pareto k estimates are good (k < 0.5).
See help('pareto-k-diagnostic') for details.
```

Figure 37. LOO estimate of product C

```
Model Info:
 function:     stan_glm
 family:       poisson [log]
 formula:      Spoiled_quantity ~ Beginning_inventory + Replenishment_quantity
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 155
 predictors:   3

Estimates:
                         mean   sd   10%   50%   90%
(Intercept)            -0.6    0.3 -1.0  -0.6  -0.2
Beginning_inventory     0.0    0.0  0.0   0.0   0.0
Replenishment_quantity  0.1    0.0  0.1   0.1   0.1

Fit Diagnostics:
           mean   sd   10%   50%   90%
mean_PPD 3.7    0.2  3.4   3.7   4.0

The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for details see help('summary.stanreg')).

MCMC diagnostics
                       mcse Rhat n_eff
(Intercept)            0.0  1.0  1868
Beginning_inventory    0.0  1.0  1791
Replenishment_quantity 0.0  1.0  2047
mean_PPD               0.0  1.0  2754
log-posterior          0.0  1.0  1363

For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence Rhat=1).
```

Figure 38. Summary of Bayesian Poisson regression model for product D

```
Computed from 4000 by 155 log-likelihood matrix

         Estimate   SE
elpd_loo   -354.6 13.3
p_loo         4.6  0.6
looic       709.2 26.6
------
Monte Carlo SE of elpd_loo is 0.0.

All Pareto k estimates are good (k < 0.5).
See help('pareto-k-diagnostic') for details.
```

Figure 39. LOO estimate of product D

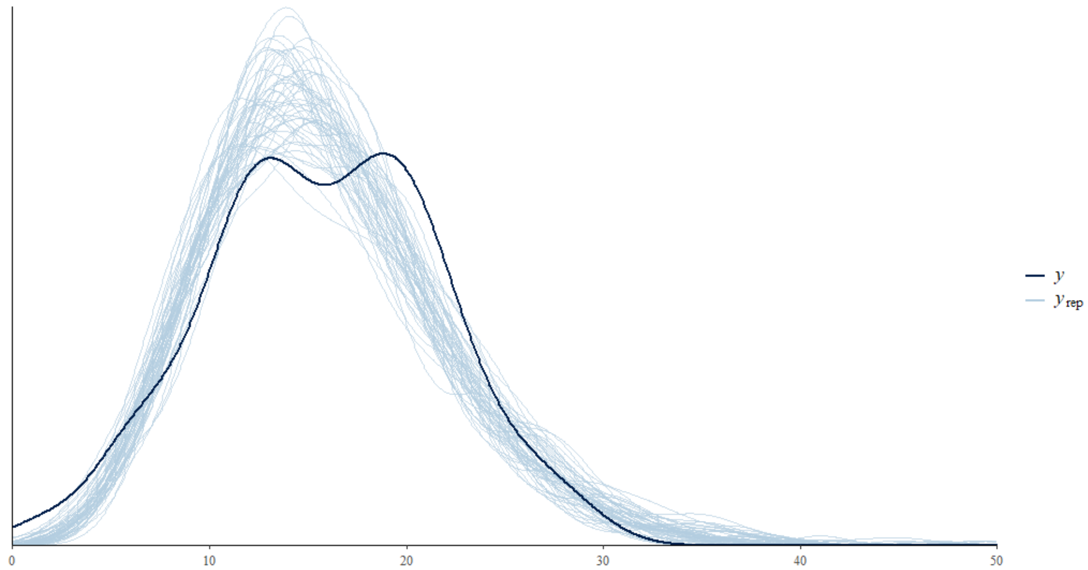

Figure 40. Posterior predictive Bayesian Poisson regression model check for product A

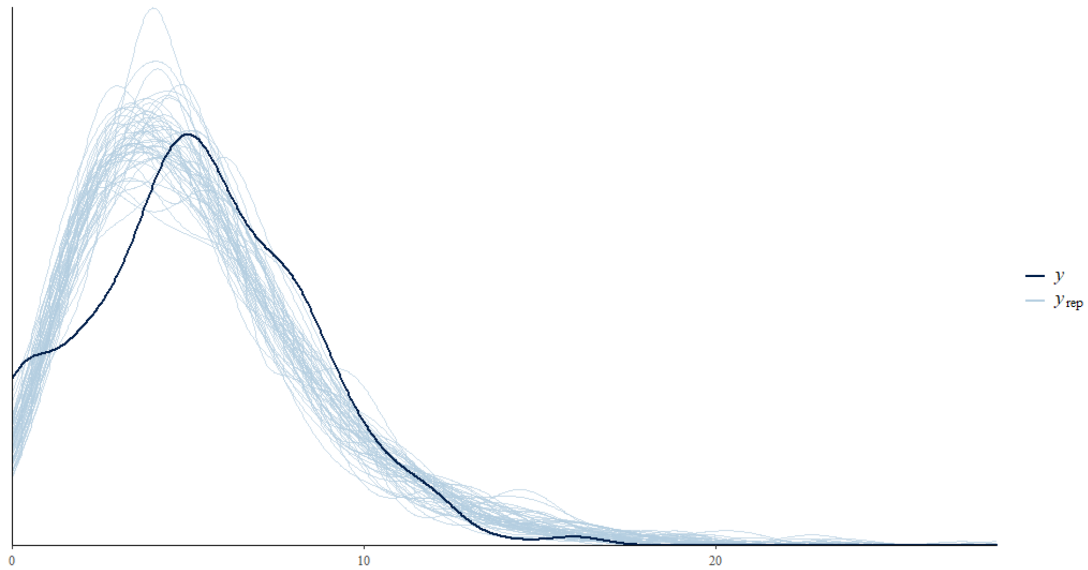

Figure 41. Posterior predictive Bayesian Poisson regression model check for product B

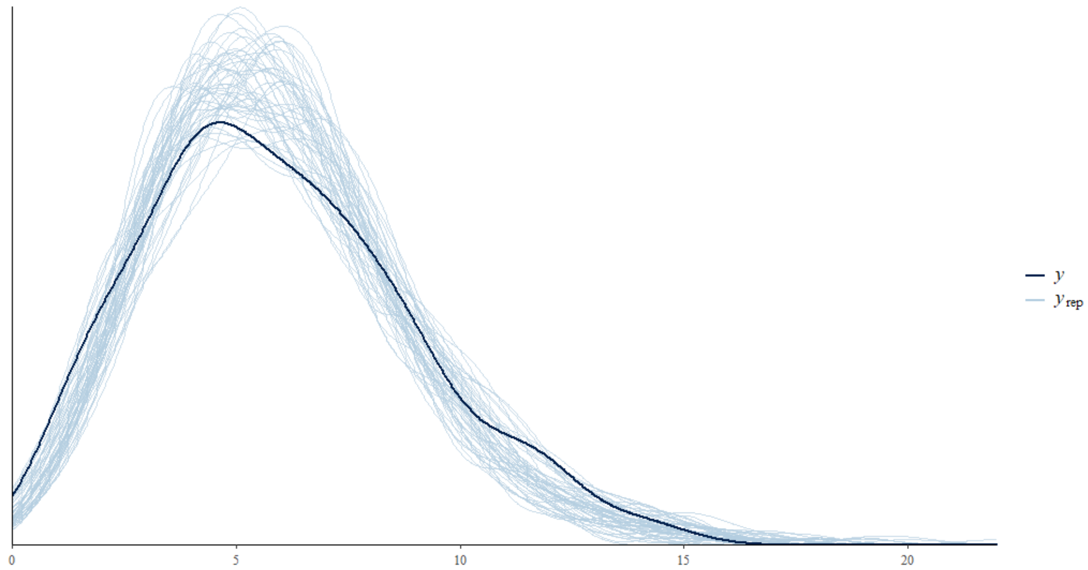

Figure 42. Posterior predictive Bayesian Poisson regression model check for product C

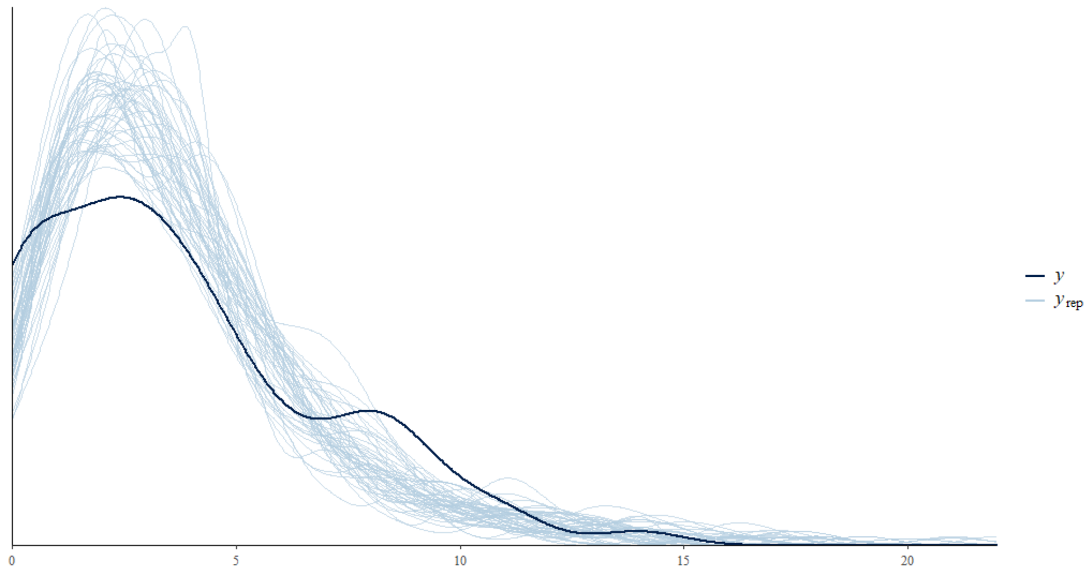

Figure 43. Posterior predictive Bayesian Poisson regression model check for product D

Appendix C. Prediction interval of test dataset using Poisson regression model for each product

Figure 44. Prediction interval of test dataset using Poisson regression model for product A

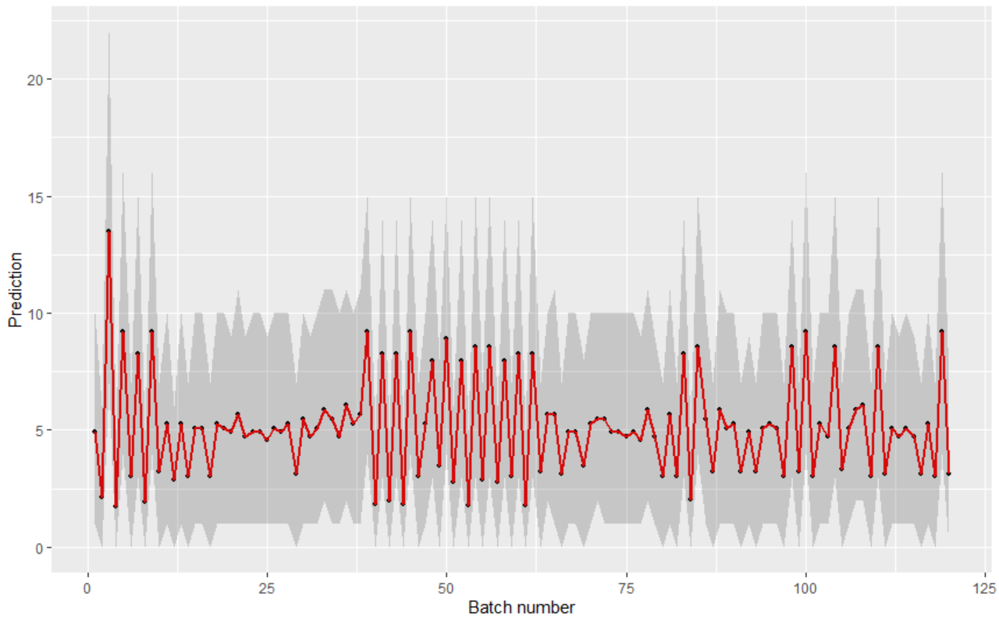

Figure 45. Prediction interval of test dataset using Poisson regression model for product B

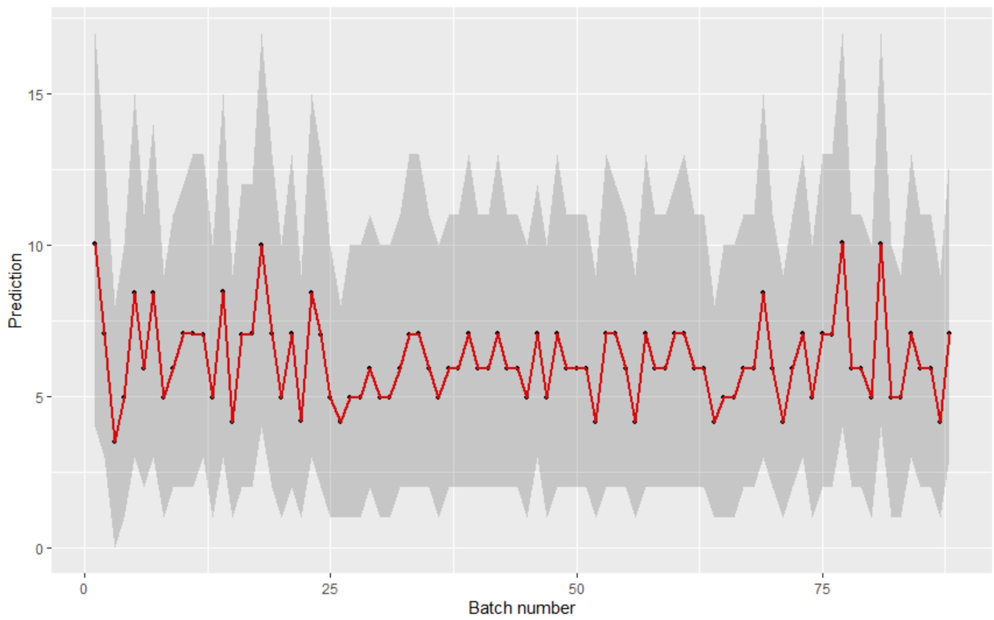

Figure 46. Prediction interval of test dataset using Poisson regression model for product C

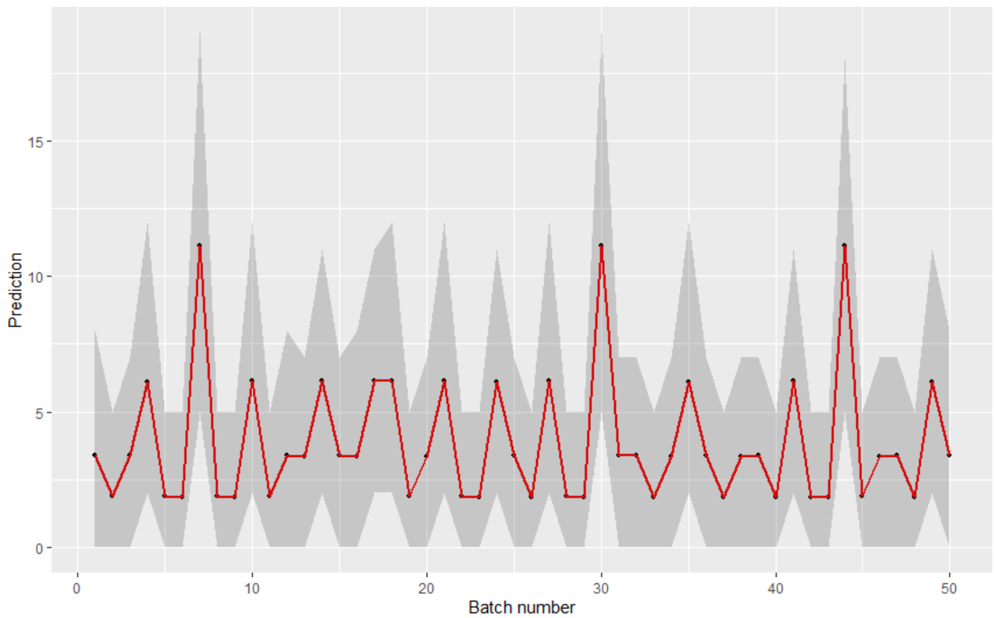

Figure 47. Prediction interval of test dataset using Poisson regression model for product D

Appendix D. Prediction interval of test dataset using Bayesian Poisson regression model for each product

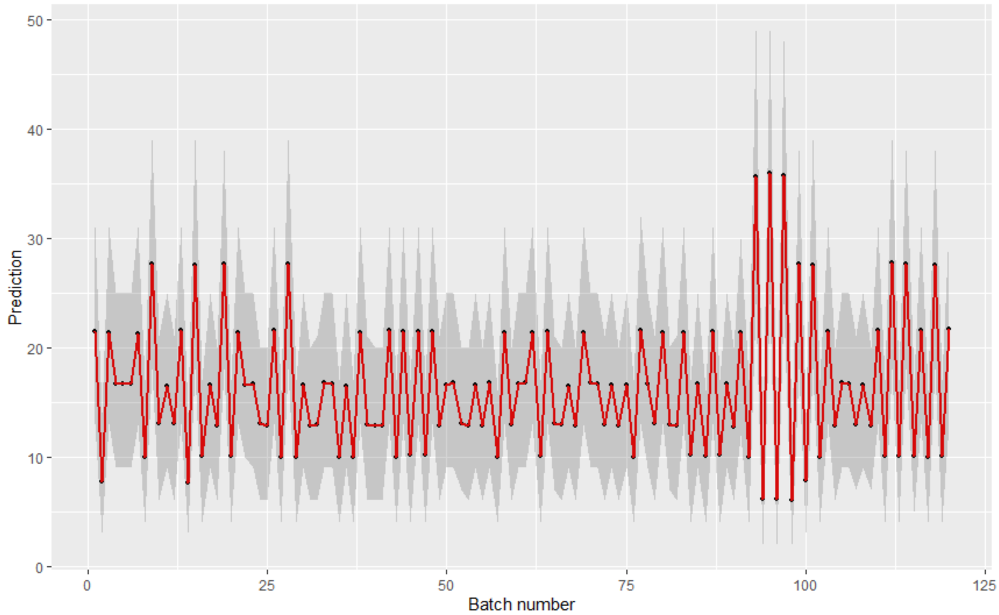

Figure 48. Prediction interval of test dataset using Bayesian Poisson regression model for product A

Figure 49. Prediction interval of test dataset using Bayesian Poisson regression model for product B

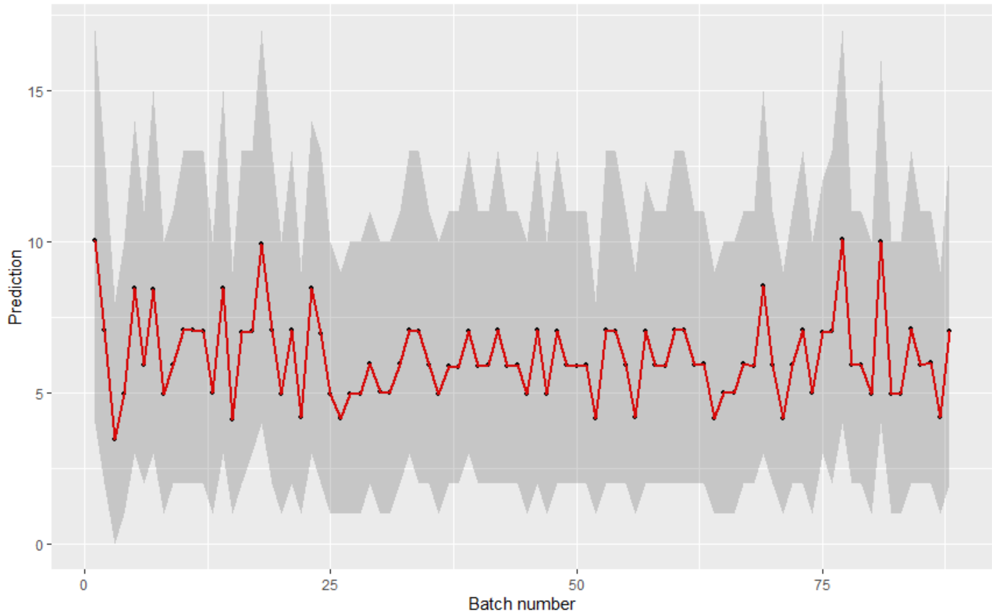

Figure 50. Prediction interval of test dataset using Bayesian Poisson regression model for product C

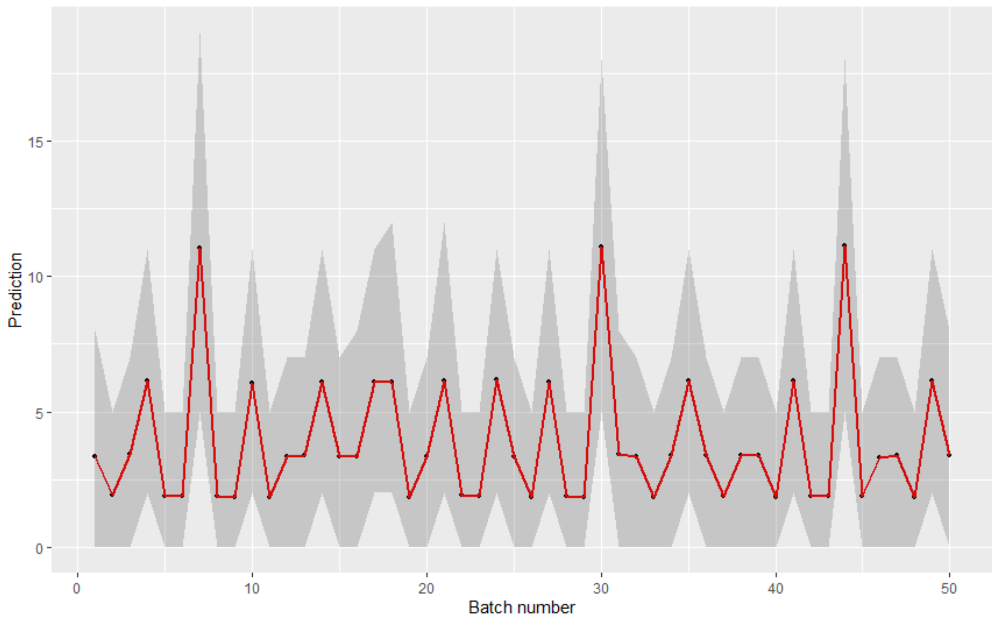

Figure 51. Prediction interval of test dataset using Bayesian Poisson regression model for product D

Appendix E. Comparison of performance measures from all approaches for each product

Table 7. Comparison of performance measures from all approaches for product A

Product	Performance measures	Poisson regression	Bayesian Poisson regression	% Diff.
A	RMSE	15.51769	4.798014	-69.08%
A	MAE	13.65273	4.01236	--70.61%
A	Bias	13.57941	-0.001677083	-100.01%

Table 8. Comparison of performance measures from all approaches for product B

Product	Performance measures	Poisson regression	Bayesian Poisson regression	% Diff.
B	RMSE	4.69353	2.206718	-52.98%
B	MAE	3.933014	1.790354	-54.48%
B	Bias	3.764726	0.1786583	-95.25%

Table 9. Comparison of performance measures from all approaches for product C

Product	Performance measures	Poisson regression	Bayesian Poisson regression	% Diff.
C	RMSE	4.207792	2.318318	-44.90%
C	MAE	3.626991	1.893048	-47.81%
C	Bias	3.463047	-0.926304	-126.75%

Table 10. Comparison of performance measures from all approaches for product D

Product	Performance measures	Poisson regression	Bayesian Poisson regression	% Diff.
D	RMSE	3.813634	2.349596	-38.39%
D	MAE	2.897845	1.846085	-36.29%
D	Bias	2.486871	-0.188815	-107.59%

Appendix F. Summary of computational complexity

Table 11. Computational times of proposed solutions

Proposed solutions	Forecasting horizon	Tasks	Product A (secs)	Product B (secs)	Product C (secs)	Product D (secs)	Total time (secs)
Poisson Regression	Long term	Gen	0.01496	0.01299	0.00798	0.01001	0.04594
Poisson Regression	Long term	Pred	0.00797	0.00696	0.00700	0.00598	0.02792
Poisson Regression	Long term	Total	0.02293	0.01995	0.01498	0.01599	0.07385
Bayesian Poisson Regression	Long term	Gen	21.39136	8.04593	21.45215	3.27979	54.16923
Bayesian Poisson Regression	Long term	Pred	0.37598	0.14562	0.12463	0.08378	0.73001
Bayesian Poisson Regression	Long term	Total	21.76734	8.19155	21.57678	3.36357	54.89924
Ratio (Bayesian (Total) / non-Bayesian (Total)			949	411	1440	210	743